On the Neuronal Systems Underlying Perceptual Decision-Making and Confidence in Humans

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To my parents

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Abstract

Perceptual decision-making refers to the ability to arrive at categorical judgments about states of the outside world. Here we use functional magnetic resonance imaging and multivariate pattern analysis to identify decision-related brain regions and address a number of open issues in the field of perceptual decision-making.

In the first study (Hebart et al., 2012), we demonstrated that perceptual decisions about motion direction are represented in both visual and parietal cortex, even when decoupled from motor plans. While in early visual cortex the amount of information about perceptual choices follows the amount of sensory evidence presented on the screen, the reverse pattern is observed in left posterior parietal cortex. These results reveal the brain regions involved when choices are encoded in an abstract format and suggest that these two brain regions are recruited differently depending on the amount of sensory evidence available.

In the second study (Hebart et al., submitted), we show that the perceptual decision variable (DV) is represented throughout fronto-parietal association cortices. The DV in right ventrolateral prefrontal cortex covaries specifically with brain signals in the ventral striatum representing confidence, demonstrating a close link between the two variables. This suggests that confidence is calculated from the perceptual DV encoded in ventrolateral prefrontal cortex.

In the third study (Christophel et al., 2012), using a visual short-term memory (VSTM) task, we demonstrate that the content of VSTM is represented in visual cortex and posterior parietal cortex, but not prefrontal cortex. These results constrain theories of VSTM and suggest that the memorized content is stored in regions shown to represent perceptual decisions. Together, these results shed light on the neuronal code underlying perceptual decision-making in humans and offer the prospect for a more complete understanding of these processes.

Zusammenfassung

Die Fähigkeit, Zustände in der Außenwelt zu beurteilen und zu kategorisieren, wird unter dem Oberbegriff „perzeptuelles Entscheiden“ zusammengefasst. In der vorliegenden Arbeit wurde funktionelle Magnetresonanztomografie mit multivariater Musteranalyse verbunden, um offene Fragen zur perzeptuellen Entscheidungsfindung zu beantworten.

In der ersten Studie (Hebart et al., 2012) wurde gezeigt, dass der visuelle und parietale Kortex eine Repräsentation abstrakter perzeptueller Entscheidungen aufweisen. Im frühen visuellen Kortex steigt die Menge entscheidungsspezifischer Information mit der Menge an verfügbarer visueller Bewegungsinformation, doch der linke posteriore parietale Kortex zeigt einen negativen Zusammenhang. Diese Ergebnisse zeigen, wo im Gehirn abstrakte Entscheidungen repräsentiert werden und deuten darauf hin, dass die gefundenen Hirnregionen unterschiedlich in den Entscheidungsprozess involviert sind, je nach Menge an verfügbarer sensorischer Information.

In der zweiten Studie (Hebart et al., submitted) wurde gezeigt, dass sich eine Repräsentation der Entscheidungsvariable (EV) im fronto-parietalen Assoziationskortex finden lässt. Ferner weist die EV im rechten ventrolateralen präfrontalen Kortex (vlPFC) einen spezifischen Zusammenhang mit konfidenzbezogenen Hirnsignalen im ventralen Striatum auf. Die Ergebnisse deuten darauf hin, dass Konfidenz aus der EV im vlPFC berechnet wird.

In der dritten Studie (Christophel et al., 2012) wurde gezeigt, dass der Kurzzeitgedächtnisinhalt im visuellen und posterioren parietalen Kortex, nicht jedoch im präfrontalen Kortex repräsentiert wird. Diese Ergebnisse lassen vermuten, dass der Gedächtnisinhalt in denselben Regionen enkodiert wird, die auch perzeptuelle Entscheidungen repräsentieren können. Zusammenfassend geben die hier errungenen Erkenntnisse Aufschluss über den neuronalen Code des perzeptuellen Entscheidens von Menschen und stellen ein vollständigeres Verständnis der zugrundeliegenden Prozesse in Aussicht.

Table of Contents

Abbreviations

BOLD	Blood oxygen level dependent
dlPFC	Dorsolateral prefrontal cortex
DV	Decision variable
EEG	Electroencephalography
FFA	Fusiform face area
fMRI	Functional magnetic resonance imaging
LIP	Lateral intraparietal area
MEG	Magnetencephalography
MT	Middle temporal area
MVPA	Multivariate pattern analysis
PPA	Parahippocampal place area
PPC	Posterior parietal cortex
RDM	Random dot motion
RF	Receptive field
RT	Response time
SDT	Signal detection theory
vlPFC	Ventrolateral prefrontal cortex
VSTM	Visual short-term memory

“La vie est la somme de tous vos choix”

(“Life is the sum of all your choices.”)

Albert Camus

1. General introduction

Whenever we interact with our environment, we are faced with decisions. Whenever there is more than one alternative, we can decide between them. A wrong decision can have quite devastating consequences, while a correct decision most often goes unnoticed. Humans can navigate through highly complex and unpredictable environments, yet they can do so without much effort and often without even noticing. Making everyday decisions such as which food to buy in the supermarket seems to be a simple matter; so simple that their investigation could be perceived as a trivial problem.

Only when we analyze the details of the decision-making process it becomes clear that decision-making is not as trivial a matter as might be thought (Gold & Shadlen, 2007; Platt et al., 2008). The detail at which people analyze decision-making can vary, and there are different theoretical ideas about how we form decisions (Kable and Glimcher, 2009). A superficial analysis would contain the following steps necessary to form a decision: The decision maker has to be motivated and physically able to carry out the decision at all. She needs to have knowledge of the different alternatives she can decide between. She needs to observe evidence about a state of the world (immediate or from memory) in favor or against any of these alternatives. Most current models assume that she would sample different pieces of evidence or that she repeatedly observes evidence, and that she finally sums up – or “accumulates” – all these pieces of evidence. Finally, she makes a decision if the evidence in favor of one option exceeds a certain response criterion, but the accumulation process and the criterion can be affected by the overall likelihood of each alternative, the expected value associated with each alternative, and other priors.

To understand these processes, consider the following example. When Miss Marple, a character from the novels of Agatha Christie, finally solves a criminal case, she explains in detail what clues ("evidence") were needed to reach a verdict against one suspect and to exonerate others. In the beginning she may have been biased towards a previously convicted suspect ("overall likelihood"), but was quite cautious making her decision (setting the "criterion" high), because she assumed that in this case having no suspect arrested would still be better than arresting a suspect who actually did not commit the crime ("decision value[1]").

Although such characters often appear to follow quite logical trains of thought to come up with a conclusion, in reality our decisions are often biased and driven by intuitions, heuristics, emotions, or more generally the way be believe the world around us works (Kahneman and Tversky, 1972). Even unconscious prior assumptions about the world, e.g. that beautiful people are nice people, can affect our decisions (Greenwald et al., 1998). It should be evident by now that decision-making is not as trivial as may be thought.

1.1 Perceptual decision-making

One form of decision-making which deals with decisions based on sensory stimuli is perceptual decision-making. Typically, in perceptual decision-making continuous sensory information is transformed into a limited number of perceptual categories, and appropriate actions are performed using the decision making processes described above.[2] Even very simple everyday decisions – such as stopping at a red light – are supposed to follow this scheme. Arriving at a perceptual decision and carrying out an action associated with a perceptual category is called a perceptual choice.

[1] To be more precise, the term *decision value* refers to the value of a decision, i.e. how much the decision is worth to the subject, a term often be mixed up with *decision variable* which will be introduced later.

[2] The description of the transformation being from continuous to discrete is in most cases accurate. Of course, sensory information can sometimes also be quite discrete which would make the decision-making process very simple, and the responses of perceptual decisions response can also take a continuum, e.g. when exerting a certain level of force to the gas pedal or steering the wheel while driving a car.

Perceptual decision-making is not only interesting in terms of choosing the appropriate action from several alternatives: It can be seen as a simple role model for more complex decisions. While it is difficult to quantify how Miss Marple accumulated her evidence based on her clues, in the field of perceptual decision-making typically a limited number of alternative choices are used, together with simple sensory information that can be varied in a continuous manner across several dimensions, e.g. color, shape, or motion direction (Gold and Shadlen, 2007). In addition, studies of perceptual decision-making are often conducted with stimulus categories and motor outputs for which brain responses are comparably well understood (Britten, 2003). The hope is that once the basic properties of simple perceptual decisions are understood, in the long run these results could be extended to more complicated scenarios (Smith and Ratcliff, 2004). Recent results suggest that this indeed is possible, by applying findings from perceptual decision-making to a larger number of response alternatives (Churchland et al., 2008), decision-making about probabilities (Yang and Shadlen, 2007), confidence about simple decisions (Kiani and Shadlen, 2009), and even economic decisions (Hare et al., 2011).

1.2 Signal detection theory

The foundation for most of today's research on perceptual decision-making – both conceptually and mathematically – can be seen in signal detection theory (Green and Swets, 1966). Originally developed in research financed by the U.S. Air Force to detect weak signals with radars (Marcum, 1948), it has later been very successfully applied to human psychophysical detection and discrimination performance (Tanner and Swets, 1954), because it offers a measure of the information available to an observer that is not confounded by decision bias. In SDT, correct and incorrect responses are treated separately based on whether a stimulus is present or absent (Figure 1A). It turns out that while the overall correctness of an observer is not ideal for indicating his ability to discriminate between presence and absence of a stimulus, SDT can be used to estimate this ability,

which is known as the *sensitivity d'*. For example, a radiologist may often be incorrect with his diagnosis: He may perform very well in telling that a subject has a tumor ("*hit*"), but be reasonably bad in diagnosing a healthy person as healthy ("*correct rejection*"). However, this has to do with what is called decision bias, also known as the decision *criterion c*. He prefers to make errors in which he falsely detects tumors ("*false alarm*"), because these errors lead him to finding a tumor more often when it is there, and such errors are in his view not as bad as falsely missing a tumor ("*miss*"). In fact, he may well be able to discriminate between a tumor and no tumor, but based on a simple analysis of correctness one could falsely conclude that the radiologist is doing a poor job in discriminating healthy from ill. The ability to discriminate refers to the extraction of sensory evidence under uncertainty, and this uncertainty stems from background noise. SDT can provide answers to the question of how well an observer performs in relating predefined categories to predefined actions and how his choice is influenced by his aptness to choose one rather than another response (Macmillan and Creelman, 2005).

In a simple signal detection scenario, each particular stimulus – whether it contains signal or not – can be treated as falling on a *decision axis* along which the observer discriminates (Figure 1B). In the simplest case, this axis is one-dimensional. Importantly, however, this axis does not need to follow one particular physical characteristic of the stimulus, but can also be seen as a line through a space spanned by an arbitrary number of stimulus dimensions (such as size, shape, color) where each dimension is differently weighted, just as long as any of these dimensions are used for making the decision and that the decisions are not weighted differently across observations. SDT assumes that an observer has some knowledge of the probability with which each stimulus will have a certain value along this axis. In other words, the observer is supposed to know the probability density functions for both stimulus classes, in our example signal present vs. signal absent. For difficult classifications, these two density functions overlap which means that an observer necessarily is going to make some mistakes. Discriminability is described as the difference between the z-transformed hit and false alarm rates:

d' = z(HR) – z(FR)

The criterion *c* refers to the point on the axis at which the observer separates between both categories (Figure 1B). The hit rate *HR* is the area under the probability density function of the signal distribution, ranging on the decision axis from *c* to infinity, the false alarm rate *FR* is the area under the probability density function of the noise distribution with the same range, and z(p) denotes the inverse cumulative Gaussian distribution. Importantly, the discriminability stays the same, no matter how the criterion is set.

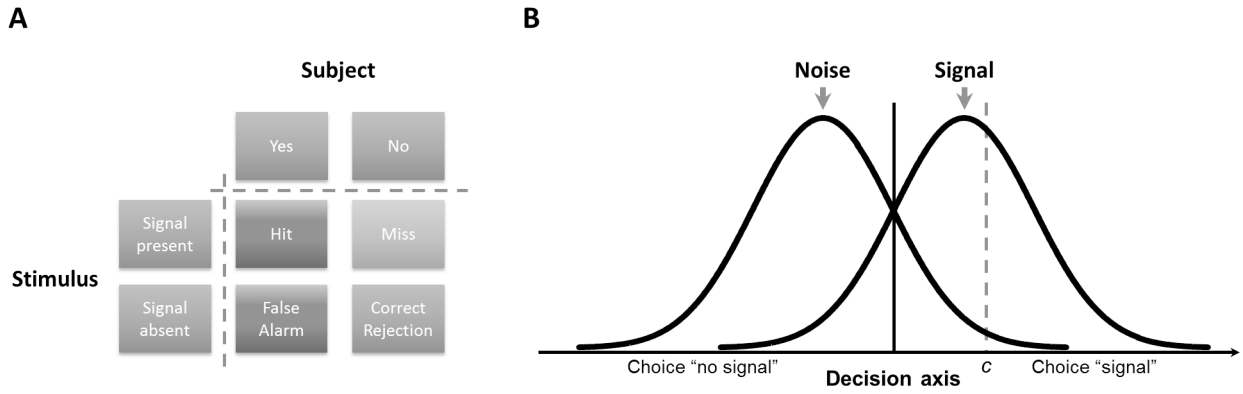

Figure 1. The signal detection theory framework. (*A)* In signal detection theory, correct and incorrect responses are treated differently depending on whether a stimulus was present or absent. This allows estimating the sensitivity of an observer in discriminating between the presence and absence of a stimulus, independent of the response criterion he applies for his choice. (*B*) According to signal detection theory, the observer decides along a hypothetical decision axis. The probability density functions denote the probability for a signal to have a specific intensity along the axis. All intensity values larger than the criterion are treated as belonging to one category (e.g. "signal present") whereas all intensity values smaller than the criterion belong to the other category (e.g. "no signal present").

SDT has been and still is one of the most valuable quantitative approaches to investigating perceptual decision-making. Nevertheless, SDT is neutral with respect to the exact instantiation of the process of evidence accumulation. In addition, this theory captures only the "performance" aspect of behavior, but does not incorporate the profile of subjects' response times which also varies depending on the difficulty of the stimulus discrimination. SDT does not provide information about the timing of events, so an extension in the time domain that can incorporate reaction times may be helpful for a more complete understanding of behavior (Gold and Shadlen, 2007). This would have another advantage: As mentioned above in the example with Miss Marple, there are different sources of priors,

including the expected value and the overall likelihood of each option which affect the accumulation of evidence and the criterion of the subject. In SDT, these sources are treated as one variable (the criterion), but a separation of them would be quite valuable in explaining behavior. Since these different priors differentially contribute to the decision making process at different points in time, they may be better distinguished using information about how the decision evolves across time. Finally, a theory of choices incorporating response times could naturally provide a framework for the speed-accuracy trade-off which refers to the fact that faster responses often come at the cost of increased error rates (Luce, 1986).

1.3 Sequential sampling models of perceptual decision-making

Sequential sampling models – also known as integrator models – can be seen as an extension of SDT in the time domain. All sequential sampling models have in common that the sensory evidence available to the observer is repeatedly sampled and accumulated across time. Repeated sampling is necessary, because the neuronal representation of sensory evidence is inherently noisy, i.e. it fluctuates randomly from moment to moment (Ratcliff and Smith, 2004). When an accumulator reaches a specified criterion a response can be executed. Thus, the accuracy is given by the criterion – or bound – that is reached, and the response time (RT) is determined by the time it takes to reach this bound plus additional non-decision time. This idea of sequential sampling and accumulation was probably introduced to psychology by Stone (1960) who based his idea on pioneering work by Wald (1947) using the so-called sequential probability ratio test. The most successful behavioral models can be separated into two classes (Smith and Ratcliff, 2004): random walk models (Figure 2A, Laming, 1968; Link and Heath, 1975; Ratcliff, 1978) and accumulator models (Figure 2B, Vickers, 1970; Usher and McClelland, 2001).

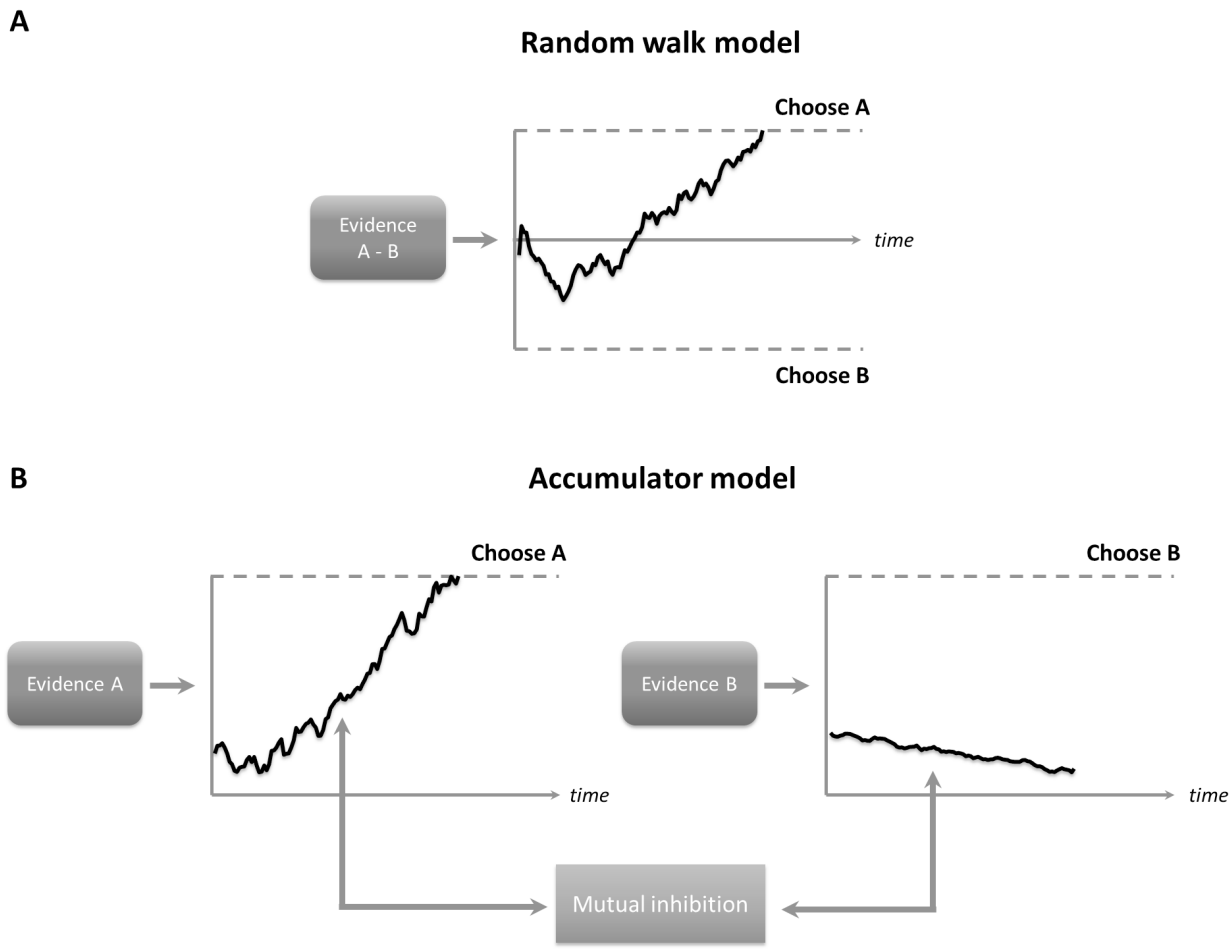

Figure 2. The two dominant sequential sampling models of perceptual decision-making. Both models assume that noisy sensory evidence is accumulated across time until a threshold is reached (dashed line) at which a choice is made and a response can be executed. *(A)* Random walk models assume that the difference of evidence at a given point in time is accumulated in a single accumulator. The threshold that is reached determines the choice. *(B)* In accumulator models, there is separate evidence accumulation for all alternatives and only one threshold for each choice. The most successful versions of these models also include mutual inhibition between the accumulators.

Random walk models assume one accumulator and two bounds in the case of two response alternatives. As soon as one of the bounds is reached, a response can be executed. Evidence is accumulated in terms of the difference between both alternatives, i.e. that evidence in favor of one alternative is evidence against the other alternative. One class of random walk models is that of drift-diffusion models (Ratcliff, 1978) which have become very popular more recently, because they can be used to explain not only behavioral (Ratcliff and Smith, 2004), but also neuronal data (Ratcliff et al., 2003) and offer analytical solutions which makes problems computationally more tractable.

Accumulator models – often also called race models – on the other hand assume one accumulator and one bound for each response alternative. Some accumulator models assume independence (Vickers, 1970; Townsend and Ashby, 1983) while others incorporate mutual inhibition at the level of the sensory evidence (Shadlen and Newsome, 2001; Mazurek et al., 2003) or at the level of the integration of sensory evidence (Usher and McClelland, 2001; Wang, 2002).

In most cases, both the drift-diffusion model (Ratcliff, 1978) and the leaky accumulator model (Usher and McClelland, 2001) perform equally well. This, however, may be due to the fact that mathematically accumulator models with inhibition and an optimal level of mutual inhibition can be reduced to random walk models (Bogacz, 2007). More recently, a third type of model has been developed which has received a lot of interest. This has to do with its simplicity and the ability to explain all known patterns of RT and performance, with even simpler analytical solutions that can be applied to more than two response alternatives: the linear ballistic accumulator model (Brown and Heathcote, 2008). However, this model suffers from neuronal implausibility, because the parameters are set and fixed at the beginning of the accumulation process which would make additional accumulation of evidence unnecessary. The model would also have a hard time incorporating non-stationary sources of noise (but see Brown and Heathcote, 2008).

Is there actually neuronal evidence that decision makers use mechanisms such as accumulation of evidence for making their perceptual decisions? In the following sections, we highlight important results in the experimental literature, but focus on experiments conducted in the visual domain (for a review of other domains, see Gold and Shadlen, 2007). Before coming to these results, we provide a brief explanation of some of the behavioral tasks used to investigate perceptual decision-making in neuroscience.

1.4 Tasks used to study neuronal processes underlying perceptual decision-making

In general, most perceptual decision-making tasks share two features: First, they measure either detection ("*is there a stimulus*?") or discrimination ("*is it stimulus A or stimulus B*?") performance using RTs or accuracy, and second they focus mainly on task difficulty levels at which subjects perform neither at floor nor at ceiling in both of these measures. We will return to the importance of this second point in Chapter 3.1.

There are various tasks that have been carried out to study perceptual decision-making (Parker and Newsome, 1998; for a review of studies related to animal and human neuroscience, see Gold and Shadlen, 2007; Heekeren et al., 2008). In most cases, studies of perceptual decision-making have been conducted in the visual domain, probably because the visual system is better studied than other sensory modalities. There are, however, a number of neuroscientific studies that have been carried out in other perceptual domains, most importantly in the tactile (Mountcastle et al., 1990; Hernández et al., 2000; Romo et al., 2004; Pleger et al., 2006), more rarely in the olfactory (Uchida and Mainen, 2003; Bowman et al., 2012) and the auditory modalities (Binder et al., 2004; Kaiser et al., 2007), or other sensory pathways such as pain (Wiech et al., 2010). However, since all experiments in this dissertation were visual experiments, we will not discuss other modalities further.

In the visual domain, the neuroscience of decision-making has also seen a number of different approaches. These approaches include detection and discrimination tasks and vary from the level of contrast discrimination (Barlow et al., 1987) and perceptual acuity (Parker and Hawken, 1987) via very simple visual stimuli such as gratings (Bradley et al., 1987; Kahnt et al., 2011) to more complex stimuli such as faces and houses (Heekeren et al., 2004; Afraz et al., 2006; McKeeff and Tong, 2007). The probably most commonly employed stimulus is a motion stimulus called random dot motion (RDM) kinematogram.

In the RDM task, subjects observe a cloud of moving dots and need to detect or report the direction of coherent motion. Between two consecutive frames, only a small percentage of dots move in the target direction, typically at a fixed speed, while motion of all other dots acts as noise. In many versions of the RDM task, target dots change randomly

from one frame to another to prevent detection of coherent motion through only a small number of dots (for review and comparison of methods, see Scase et al., 1996; Pilly and Seitz, 2009). The most common movement of all noise dots is movement in random directions fixed across time ("direction noise"), movement in random directions varying across time ("Brownian noise") or movement with positional displacement which is identical to both random directions and random speed varying across time ("white noise", Britten et al., 1992). In addition, there are combinations of these displacement methods where each dot receives a limited lifetime, and interleaved sequences in which displacements happen across multiple frames, rather than between two successive frames (Shadlen and Newsome, 2001).

The amount of signal, i.e. how strong the target motion direction is represented in the stimulus, is typically defined as the percentage of dots moving in the same direction and is termed the motion coherence. The RDM stimulus has become quite popular among vision scientists and researchers interested in investigating the neuronal mechanisms subserving motion perception (Britten et al., 1992), perceptual decision-making (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002), and perceptual learning (Ball and Sekuler, 1982; Watanabe et al., 2002). One of the reasons for this popularity stems from the ease of manipulating the difficulty of the stimulus to achieve very small differences in performance around the perceptual threshold. Another aspect that is particularly important for researchers investigating the time-course of perceptual decision-making in sequential sampling models is the necessity to observe the stimulus for longer periods of time in order to perceive the target motion, which in other stimuli might be more difficult to manipulate. Finally, within the visual system motion is a perceptual feature that has been particularly well characterized at the neuronal level (Britten, 2003; Born and Bradley, 2005).

1.5 The neuronal representation of sensory evidence

First discussed in Presocratic philosophy (von Glasersfeld, 1996), and formalized through the advent of psychophysics (Gescheider, 1997), it is today widely accepted that there is no direct relationship between visual stimuli in the outside world and our visual perception, i.e. that the neuronal firing patterns do not faithfully represent the world as such. The evidence that is used to guide our perceptual choices, therefore, is *sensory evidence*, i.e. evidence stemming from our senses, and is the product of neuronal signals that have been filtered and multiplexed with other neurons from the level of receptors to neurons in higher levels of the cerebral cortex. A great deal of interest has been invested into understanding the level at which neuronal responses no longer follow the "true" physical stimulus and match the way in which the stimulus is perceived. Two parallel streams of research have evolved investigating this question: One is more closely related to the properties of single neurons or neuronal populations (Parker and Newsome, 1998), uses methods from psychophysical and signal detection theory traditions (Green and Swets, 1966; Britten et al., 1992), and is mostly interested in understanding the neuronal processes governing behavioral choices of observers. The other stream investigates these neuronal processes in terms of "consciousness" (Crick and Koch, 1990; Rees et al., 2002) and involves more generally the processes minimally sufficient for a person to be conscious. In the latter approach it is, however, often (mistakenly) assumed that processes related to the perceived stimulus are processes directly involved in consciousness.[3] This tradition focuses less on the behavioral choices of subjects, but more on the aspect of subjective perception which in terms of signal detection theory can differ from behavioral choices depending on the response bias (Kanwisher, 2001).

[3] From a theoretical point of view, the relationship between how the stimulus is perceived and neuronal response patterns following this percept can be seen a necessary, but not as a sufficient requirement for consciousness. This is empirically supported by studies demonstrating correlations between perceptual decisions and neuronal responses averaged across many trials. In these studies, behavioral and neuronal data were acquired in different sessions and neuronal measurements were recorded under anesthesia, therefore demonstrating correlations of perception and neuronal activity without consciousness (Tolhurst et al., 1983; see e.g. Bradley et al., 1987).

Within the former tradition, from the early 1980's there have been multiple attempts to describe a link between the perceiver's sensitivity on the one side, and the neuronal sensitivity on the other side (for early attempts, see Parker and Hawken, 1985; Bradley et al., 1987; Barlow et al., 1987). The first direct link between monkey electrophysiology and psychophysics was achieved with concurrent measurements in both modalities (Newsome et al., 1989; Britten et al., 1992), an approach which was later extended to human observers and fMRI (Ress et al., 2000; Ress and Heeger, 2003). Newsome and colleagues (1989) demonstrated a close match psychophysical performance of macaque monkeys with firing rates of individual neurons in the middle temporal area (MT) – a region known for its strong selectivity for motion direction (Dubner and Zeki, 1971; Zeki, 1974; Born and Bradley, 2005). This means that monitoring a very small number of neurons in area MT would be sufficient to carry out the perceptual task, supported by studies applying microstimulation to area MT (Ditterich et al., 2003). However, it later became clear that this original claim only held for the average firing rate and could barely explain trial-by-trial variability in performance (Britten et al., 1996). In other words, the choice probability, i.e. the sensitivity of a single neuron in discriminating between choices given a particular stimulus, was rather low.[4] Therefore, a direct read-out of activity from individual neurons in area MT was not seen as sufficient to explain psychophysical performance (Shadlen et al., 1996).[5] Instead, other brain regions were targeted to investigate the pooling and integration of opposing motion directions.

[4] More precisely, choice probability refers to accuracy of an ideal observer to indicate the choice on a given trial by using the neuronal response.

[5] More recently, this discrepancy between extraordinarily high sensitivity of individual neurons – often higher than that of the observer – and very low choice probabilities was explained by two shortcomings of the original studies: (a) long viewing durations in the original studies, probably not mirroring the use of information of the monkey (Roitman and Shadlen, 2002), and (b) wrong assumptions about noise correlations between neurons with opposite preferred directions in area MT (Cohen and Newsome, 2008, 2009).

1.6 Neuronal evidence for evidence-accumulation mechanisms in the macaque monkey

A primary candidate for an integrator region was the lateral intraparietal area (LIP) which lies midway in the hierarchy between area MT encoding sensory evidence and motor regions such as the frontal eye field and the superior colliculus that directly participate in eye movement responses (Shadlen and Newsome, 2001). Today, there is good evidence that for eye-movement tasks, area LIP not only accumulates sensory evidence, but closely tracks the formation of the decision, in other words carries a time-varying representation of a perceptual decision variable (DV, Gold and Shadlen, 2007). In decision-making tasks, LIP neurons are selected based on their response in a memory-guided saccade task (Colby et al., 1996). Typically, a visual target stimulus (e.g. a colored disk) is placed into the receptive field (RF) of a neuron, and neuronal responses are measured to this stimulus. This means that increases in firing rates to the stimulus reflect increased processing of the target stimulus, which can be used as an index of sensory evidence accumulation. There are numerous studies together implicating that the region might carry a perceptual DV (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Hanks et al., 2006; Churchland et al., 2008; Kiani and Shadlen, 2009; Bollimunta et al., 2012). They also strongly support the drift-diffusion model of perceptual decision-making (Ratcliff, 1978; Mazurek et al., 2003):

(a) When the eye-movement target which indicates the chosen direction of motion lies in the RF, neuronal firing rates increase, but they don't change or even decrease when the chosen target is not in the RF, demonstrating a choice-related response (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Churchland et al., 2008; Kiani and Shadlen, 2009; Bollimunta et al., 2012).

(b) Rather than showing constant firing rates across time as is the case for area MT, the neuronal firing rates increase steadily with time, in line with a summation response (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Churchland et al., 2008; Kiani and Shadlen, 2009; Bollimunta et al., 2012).

(c) The neuronal firing rates vary systematically with choice difficulty as expected from a time-evolving DV (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Churchland et al., 2008; Kiani and Shadlen, 2009).

(d) The firing rates predict monkeys' choices independent of whether the response was correct or incorrect (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Churchland et al., 2008).

(e) In contrast to area MT, the choice probabilities of individual neurons in LIP even for 0% coherence are very high, evolve over time and vary systematically with choice difficulty (Shadlen and Newsome, 2001).

(f) Variability in saccadic response properties (e.g. speed of saccade) are not explained by firing rates in LIP, arguing against a representation of the motor-response itself (Shadlen and Newsome, 2001; however, LIP could still convey a coarser motor signal, but see below).

(g) LIP activity increases and remains high until a response is made, at which point activity decays rapidly, indicating that the DV is only maintained until a response is made (Shadlen and Newsome, 2001; Kiani and Shadlen, 2009).

(h) When monkeys are allowed to respond as soon as they have accumulated enough evidence (RT version of the task), the relationships in (a) to (e) hold, demonstrating that the LIP response is not merely a consequence of the decision that has been formed earlier in time and has been computed elsewhere (Roitman and Shadlen, 2002; Churchland et al., 2008).

(i) LIP activity in the RT version of the task increases until a threshold, at which an eye-movement response is executed. Same as (g) this indicates that the DV is maintained until a response is made (Roitman and Shadlen, 2002; Churchland et al., 2008; Bollimunta et al., 2012).

(j) Microstimulation of area LIP biases choices towards the RF of stimulated neurons, demonstrating that LIP responses are causally involved in the decision-making process (Hanks et al., 2006).

(k) Microstimulation of area LIP never directly evokes saccades, i.e. LIP activity is not merely motor-related (Hanks et al., 2006).

(l) The firing rates increase faster when the monkey responds sooner, in line with faster accumulation of evidence on trials with shorter RT (Roitman and Shadlen, 2002).

(m) More alternatives for decision-making are reflected in lower initial firing rates, in line with a lower starting point of evidence accumulation (Churchland et al., 2008).

(n) When the monkey is given the opportunity to opt-out when it is unsure, the responses of LIP neurons are lower, in agreement with a graded representation of the DV (Kiani and Shadlen, 2009).

(o) When recording concurrently from multiple units in area LIP, the gradual increase in firing rates holds for individual trials, demonstrating that previous findings that report averaged responses over many trials are not a confound of this averaging procedure (Bollimunta et al., 2012).

Neuronal responses in other brain regions have been shown to carry activity consistent with a DV, including the dorsolateral prefrontal cortex (Kim and Shadlen, 1999; dlPFC, Hussar and Pasternak, 2013), the frontal eye field (Gold and Shadlen, 2000, 2003), and the superior colliculus (Horwitz and Newsome, 1999, 2001). However, less is known about the capacity of these brain regions to represent a DV. For example, microstimulation of both the superior colliculus and the frontal eye field evoke saccades (Schiller and Stryker, 1972; Bruce et al., 1985), but this does not necessarily affect these regions' capacity for representing a DV in a saccade task.

Other than only being related to eye-movements, area LIP has been found to be active in a number of tasks related to top-down attention (Colby et al., 1996), attentional salience (Gottlieb et al., 1998; Bisley and Goldberg, 2003), working memory (Gnadt and Andersen, 1988), relative action probabilities (Yang and Shadlen, 2007), intention (Bracewell et al., 1996; Mazzoni et al., 1996), and expected value (Platt and Glimcher, 1999). One underlying principle of LIP function could be the selection of an eye-movement target (Gold

and Shadlen, 2007), i.e. that area LIP codes for the behavioral relevance of a particular spatial location. More recent work suggests a more flexible role of this region (e.g. Freedman and Assad, 2006), in that it is involved in multiple independent computations, even within the same neuron (Bennur and Gold, 2011). Interestingly, the idea that an area which implements target-selection is also recruited to accumulate evidence does not necessitate a central decision maker that relays the outcome of a decision to other brain regions. In other words, LIP activity could reflect an embodied version of a decision, where the decision for a specific motion direction in the RDM task might be identical to the choice of the eye-movement target (O'Regan and Noë, 2001; Shadlen et al., 2008; Freedman and Assad, 2011).

So far, we did not discuss aspects of decision-making other than accumulation of evidence, and how they may be implemented in the macaque brain. For example, a general bias for one over the other option could be represented as a selective shift of the response criterion for the biased option, but also as a shift of the firing rate. Indeed, recent results indicate that changes in response criterion are signaled by changes in the firing rate of neurons in LIP (Rao et al., 2012; Rorie et al., 2010; see Platt and Glimcher, 1999, for earlier evidence), probably originating in caudate nucleus of the basal ganglia (Ding and Gold, 2010, 2012). The speed-accuracy tradeoff could be realized by a lowered threshold for responding or by generally increased firing rates of all response-selective populations of neurons which are equivalent in most models of perceptual decision-making (Bogacz et al., 2010). Other possibilities encompass non-linear changes in firing rate when evidence in favor of one response alternative increases (Hanks et al., 2011), or a modulation of the weight of evidence by an urgency signal (Cisek et al., 2009). In fact, the story might be more complicated, with recent evidence indicating both increases in baseline firing as well as increases in the rate of evidence accumulation, but no change in threshold (Heitz and Schall,

2012).[6] Another origin of the speed-accuracy tradeoff has been suggested to lie in the basal ganglia (Bogacz et al., 2010).

Taken together, there is good evidence from the literature of monkey electrophysiology that perceptual decisions are carried out by accumulating sensory evidence until a threshold at which a response is executed, and when immediate responses are not possible the accumulated evidence is maintained in the same region. For oculomotor responses, such signals have been reported in the dorsolateral prefrontal cortex, superior colliculus, the frontal eye field, and area LIP, the last of which lies between sensory and motor regions and is seen as a good candidate for representing perceptual decisions. Although the *existence* of this decision-making mechanism is not disputed, the *implementation* is still a matter of debate: While all of these brain regions show activity consistent with continuous accumulation, it is still unclear if any of these regions alone performs the summation response, if other regions carry out this computation, or even if evidence accumulation is a neuronally more distributed process (Gold and Shadlen, 2007).

1.7. Questions in the study of perceptual decision-making left open by monkey electrophysiology

Although many important questions about perceptual decision-making have been addressed by electrophysiology experiments with macaque monkeys, several questions remain. First, do the mechanisms found in macaques generalize to human observers? For example, would we find similar responses in a human homologue of monkey area LIP which has been suggested to be posterior intraparietal sulcus (Silver and Kastner, 2009)? It is unlikely that there is a strict mapping between macaque and human parietal cortex, given differences in anatomy (e.g. size, structure and connectivity), as well as function (Orban et al., 2004; Grefkes and Fink, 2005; Culham et al., 2006). For example, the commonly observed

[6] The increased drift rate suggests that in such cases observers are able to more accurately accumulate sensory evidence, i.e. they can better suppress sources of noise. Indeed, Heitz and Schall (2012) provide evidence that already sensory processing is affected by speed-accuracy tradeoff.

attentional deficit in humans termed visuospatial neglect cannot be found in macaque monkeys with lesions to the parietal cortex (Husain and Nachev, 2007).

Second, how strong is the influence of behavioral training on these neuronal response patterns? Monkeys are typically trained extensively for weeks to months to perform a perceptual decision-making task, and it has been shown that the repeated coupling of specific percepts with specific motor-responses (e.g. “always make saccade to right target when motion direction is to the right”) can lead to changes in the neuronal response properties of the superior colliculus (Horwitz et al., 2004). Whether the idea of “embodied cognition” as exemplified in oculomotor regions of LIP extends to less trained observers is left largely open by the animal literature.

Third, although there is strong evidence for the suggested regions in participating in perceptual decision-making, it is unclear if perceptual decisions are generated in these regions or if the neuronal firing patterns in these regions reflect only the consequence of a decision-making signal generated elsewhere in the brain. Even studies demonstrating that microstimulation of a particular brain region leads to changes in decision-making cannot provide a sufficient answer to this question. It has been shown that when neurons in a region – e.g. LIP – are stimulated for the entire viewing period of a stimulus, then there is a bias towards making a saccade to the RF of the stimulated neuron that indicates a choice towards that location (Hanks et al., 2006). This could mean one of three things: Either neuronal responses from area MT are pooled and summed up in area LIP, i.e. as suggested by most monkey electrophysiology studies evidence to execute a saccade is accumulated in this region; then stimulation would cause a bias of evidence towards the stimulated RF. Alternatively, area LIP might be coding the selection of an eye-movement response alone, and provided with specific input for a hypothetical decision-making region, the microstimulation-induced elevated firing rate would more readily lead to the generation of a

saccade even though the monkey's choice would not have been determined yet.[7] Another possibility is that activity in LIP might be tied to the particular type of decision made, but there may still be a more general decision-making module somewhere else in the brain.

Fourth, and related to the previous argument: Which brain regions participate in perceptual decision-making when decisions are not carried out with saccadic responses? Are there more general decision-making mechanisms that possibly also generalize across modality? Evidence from a vibrotactile discrimination task in which monkeys reported their choice with a button-press indicates that the ventral premotor cortex can be involved in computing the DV (Romo et al., 2004), but to date no monkey electrophysiology study looked at whether the DV could be represented independent of the response effector.

The use of neuroimaging techniques in humans might help providing answers to these questions. While neuroimaging suffers from lower spatial or temporal resolution than single-cell recordings, one advantage lies in the possibility to measure activity from all regions of the brain at the same time which could help identifying candidates for perceptual decision-making related brain regions. In addition, training in human observers can be done within minutes to hours and more complicated task designs are possible, while training even for simple designs in monkeys usually lasts weeks to months, bringing with it the above-mentioned problems of structural changes that might conceal the patterns of decision-making related brain activity present under normal viewing conditions (Horwitz et al., 2004).

1.8 Evidence for perceptual decision-making from human functional neuroimaging and electrophysiology

One of the first pieces of neuronal evidence for perceptual decision-making in humans came from a functional magnetic resonance imaging (fMRI) study using a face-house

[7] These scenarios could potentially be distinguished by LIP microstimulation that happens only for brief periods of time at the beginning of the trial which – if LIP really sums up responses over time – should induce the same sort of bias, but if LIP coded only the outcome of the decision, the elevated firing rates should decrease again. However, the effects found in the previous study (Hanks et al., 2006) were indeed not very large which would under temporary stimulation make it even less likely to find such an effect.

discrimination task (Heekeren et al., 2004). FMRI suffers from a much lower temporal and spatial resolution than single cell recordings which makes it difficult to observe the same sort of evidence as reported in monkey electrophysiology work which mainly relies on the temporal evolution of the signal (Chapter 1.6). This issue is explained and dealt with in more detail in Chapter 2.

One marker of evidence accumulation that might also be found in fMRI studies would be an increased blood oxygen level dependent (BOLD) signal for easier decisions, since accumulated evidence is expected to remain at a high level until a response is made, and the response threshold should be reached earlier when accumulation happens faster. The authors used a second marker by applying the following reasoning: Sensory evidence for faces should be represented in the face-selective region termed fusiform face area (FFA, Kanwisher et al., 1997), while evidence for houses should be represented in the place-selective region termed parahippocampal place area (PPA, Epstein and Kanwisher, 1998). If evidence is accumulated by a drift-diffusion-like process as explained above (Chapter 1.3), then neuronal populations carrying out such a process should represent the sum of the difference of the signals in FFA and PPA, and assuming that roughly the same number of neurons respond to face evidence than to house evidence, the *absolute* difference of both FFA and PPA signals is most informative.[8] The authors reported that both of these criteria – stronger responses to higher evidence and were fulfilled by left dlPFC and that activity in this region also predicted behavioral performance of subjects. However, given that the difficulty of decisions is correlated with the absolute difference of signals in FFA and PPA, it is unclear if the signal in dlPFC reflects decision-making as such or merely processes related to task difficulty (Tosoni et al., 2008). This problem is dealt with in more detail in Chapter 2.

The investigation of decision-making mechanisms has since seen a remarkable rise with a large variability of approaches. An in-depth review of all these studies and the applied

[8] In fact, the authors only used the difference of the signal in FFA and PPA, not the sum of the difference. However, given the sluggishness of the BOLD response and the short viewing times of stimuli, the signal in FFA and PPA would probably already represent the sum over a specific time period.

methods is beyond the scope of this dissertation (for a review of human decision-making studies in general, see Heekeren et al., 2008; for a review of studies on the speed-accuracy trade-off, see Bogacz et al., 2010). In Chapter 2 we will discuss some of these approaches and their limitations, and suggest possible solutions to some of these limiting factors.

2. How to identify perceptual decision-making related brain signals with fMRI in humans

Monkey electrophysiology research has laid the basis for the investigation of the neuronal mechanisms underlying perceptual decision-making. It provided strong evidence that decisions are formed by continuously accumulating sensory evidence over time until a threshold is reached at which time a response can be executed (Gold and Shadlen, 2007). While the existence of this mechanism in the brain is largely undisputed, its generality in perceptual decision-making has been called into question (Uchida et al., 2006; Gold and Shadlen, 2007), and it still remains unclear which brain regions carry out the process of accumulating sensory evidence and represent a decision variable (DV). A strong research focus lies on the lateral intraparietal area (LIP) of the macaque monkey (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Hanks et al., 2006; Churchland et al., 2008; Kiani and Shadlen, 2009; Bollimunta et al., 2012), but as pointed out above, current evidence is not conclusive regarding the generality of the involvement of this brain region in perceptual decision-making, i.e. whether evidence accumulation takes place in LIP only when eye-movement responses are carried out. This question might be addressed by clever future electrophysiology experiments. Current experimental evidence can show only the *participation* of this region in oculomotor decision-making, not whether the accumulation process *itself* takes place in this region. This would require the concurrent monitoring of activity of multiple candidate brain regions that are possibly unknown to the monkey electrophysiologist. In addition, it is unclear if the suggested homologies of brain regions between macaques and humans hold (Orban et al., 2004; Grefkes and Fink, 2005; Culham et al., 2006), which necessitates direct observations of human decision behavior. Human neuroimaging experiments have the potential to identify these candidate brain regions that may participate in perceptual decision-making and additionally offer the possibility to

investigate interactions between brain activity patterns in several brain regions at the same time, which together might provide a more complete picture of the decision-making process.

2.1. Inference and the link between neuronal responses and cognitive processes

Monkey electrophysiology and human neuroimaging are similar in their general approach of linking decision-making behavior to neuronal responses (Figure 3): They try to *infer* the cognitive process of interest (e.g. evidence accumulation) from neuronal and behavioral data, in that way demonstrate both the fact *that* the brain carries out this process and *where* it is carried out, which should enlighten us *how* the process is realized in the brain. This inference is not trivial, because multiple cognitive processes are present at a given time. For that reason, it is necessary to search for behavioral and neuronal effects that can *only* be explained by the suggested cognitive mechanism, or at least where alternative explanations are much less plausible (for a discussion of this topic, see Sarter et al., 1996; Poldrack, 2006). This general strategy can also be described as identifying one or several neuronal *markers* that agree or disagree with the assumed cognitive process. The reasoning is that if a marker agrees with the assumed cognitive process, but partially or fully disagrees with all alternative explanations, then the inference that the measured neuronal activity participates in the cognitive process is likely to be true. The more markers agree with the cognitive process and disagree with other processes, the larger the likelihood of the inference being correct.[9]

[9] The difficulty lies in the fact that one or several markers needs to disagree with all other cognitive processes which cannot easily be shown, in particular not in a small set of experiments.

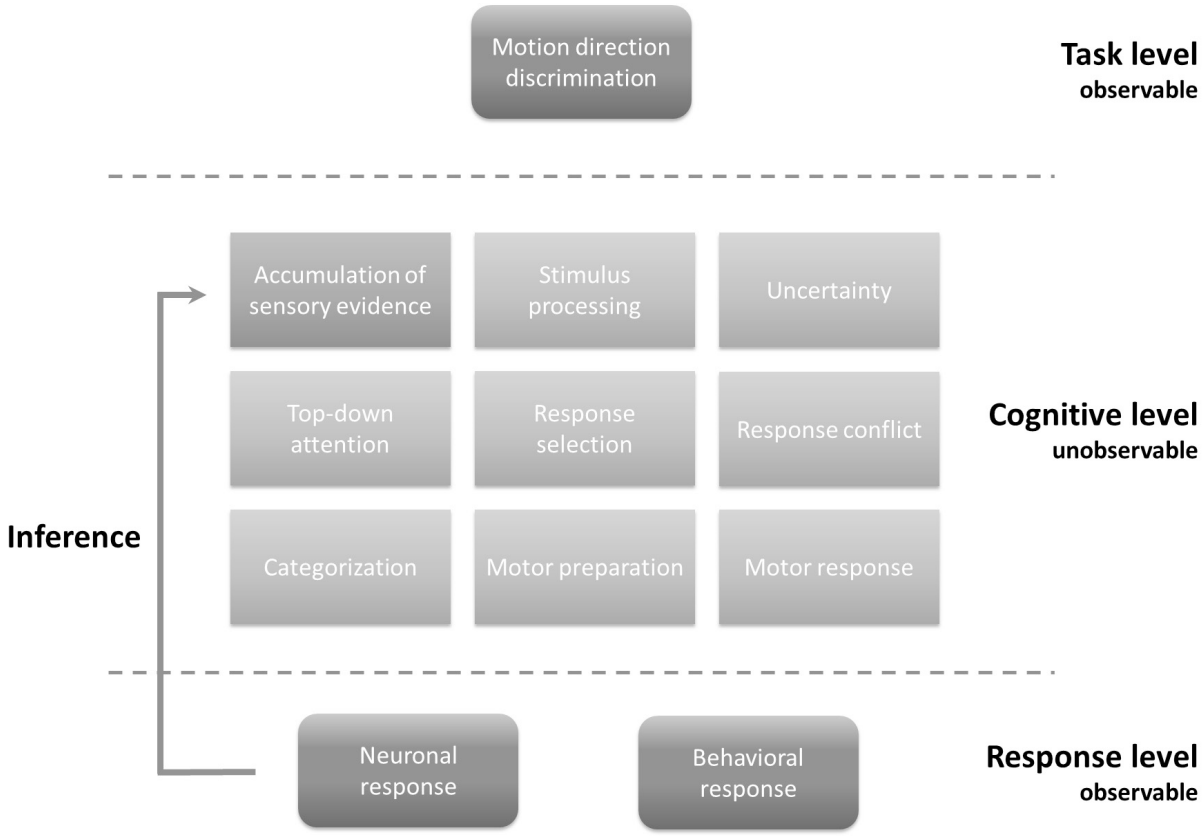

Figure 3 The inferential process in perceptual decision-making tasks. The researcher may aim at identifying the neuronal processes underlying the accumulation of sensory evidence. Based on the behavioral responses of a subject and the related neuronal responses in a particular brain region, this mechanism is assumed to be represented in a particular brain region. The inference can, however, only be made if all other cognitive processes that happen at the same time interval cannot explain the neuronal and behavioral response pattern.

2.2 The different levels of description for decision-related neuronal processes

A crucial distinction to be made at this point is about different levels at which decision-related neuronal processes can be described, something that may often be confused if not spelled out explicitly (Figure 4). Here, the distinction is made between four levels of description: decision-related, decision-relevant, decision-specific, and decision-implementing neuronal processes. The description is hierarchical, i.e. decision-implementing neuronal processes are a subset of decision-specific processes, and decision-specific processes are a subset of decision-relevant processes, etc.

Decision-related neuronal processes are all those processes that generally participate in the decision-making process. They show changes in their response when a

decision is carried out, and their manipulation can have an influence on the dynamics of the decision. An example for processes that would only qualify as being decision-related are attentional processes that could have an impact on the decision-making process, but which are not strictly necessary for decision-making. *Decision-relevant* processes are similar to decision-related processes, but they are indeed crucially involved in the decision, i.e. they are relevant for a decision and without them a decision could not be executed. For example, the representation of sensory evidence and the motor response initiation are critical parts of a decision-making process, but neither require that a perceptual decision is carried out at the same time. That means the presence of these processes is not sufficient for the presence of decision-making.[10] *Decision-specific* processes are those processes that carry a DV, i.e. they can be used to predict the choice of a subject on any given trial; also without these processes a decision could not be carried out. Any brain region representing a DV would qualify as decision-specific. Finally, *decision-implementing* processes are those processes that are critically involved in the creation of a DV, i.e. they carry out the transformation process of other cognitive variables into a DV.

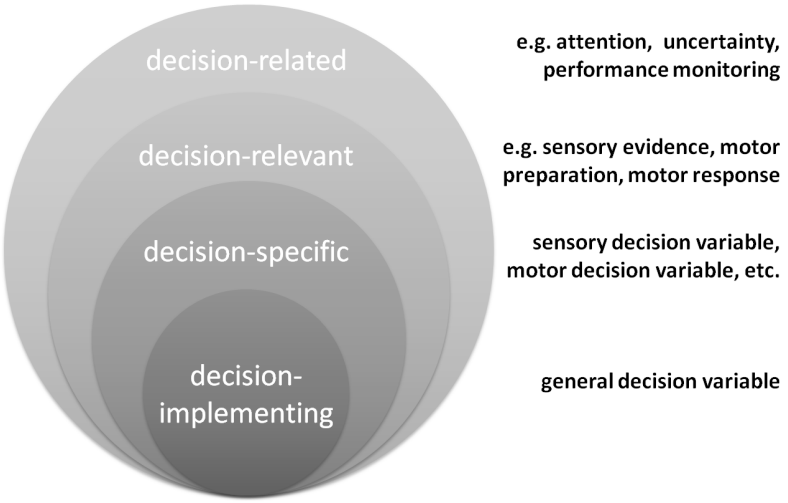

Figure 4 A taxonomy of decision-related neuronal processes, representing different levels of description and specificity of the relationship between perceptual decision-making and neuronal response patterns. The more specific processes can be seen as part of the more general processes.

The distinction between decision-related and decision-relevant is somewhat vague, because some attentional processes are of course necessary for the execution of a decision. However, they can also be seen as an enabling factor for the existence of decision-relevant,

[10] As a side remark, if the DV was represented in an embodied manner (Shadlen et al., 2008), i.e. if making a decision was implemented in a motor planning scheme, then the presence of motor planning would indicate that a decision is being made.

decision-specific, and decision-implementing processes. Also the border of decision-relevant and decision-specific is soft, because for a given task and a given motor response the DV might be mirrored only in regions of the saccadic system, whereas in the same task with a different motor response the DV might only be reflected in regions of the grasping system. In that case, decision-implementing processes would be identical to decision-specific neuronal processes. Although these borders might be soft, we believe the taxonomy is useful for a clearer description of neuronal processes underlying perceptual decision-making.

How far are we in the description of these processes? In the next two sections, neuronal markers of monkey electrophysiology and human neuroimaging are compared. As we will see, neither method has clearly reached the highest level of description, but human neuroimaging experiments are at the moment much less advanced than monkey electrophysiology. We will propose that some of these limitations in human neuroimaging can be avoided by the use of multivariate pattern analysis (MVPA, Haxby et al., 2001; Haynes and Rees, 2006), offering an avenue to bridge the gap between the description of these processes across species.

2.3. Decision-related brain signals in monkey electrophysiology

Neuronal markers of decision-related processes have been reported in a number of monkey electrophysiology experiments. A now classical example is the choice probability introduced by Britten, Newsome and colleagues (Britten et al., 1996) which denotes the ability of a single neuron to discriminate between the choices of a subject given a particular stimulus (see Chapter 1.5). The choice probabilities found in motion-sensitive area MT were generally quite low (Purushothaman and Bradley, 2004; see also Cohen and Newsome, 2009), disqualifying single neurons of area MT as the neuronal site at which decisions are implemented. Even if choice probabilities were high in populations of MT neurons, they are typically calculated across the entire viewing window. This summing mimics the process of evidence accumulation, and if any would provide evidence for MT as carrying the sensory

evidence that might be integrated somewhere else. This still means that activity in area MT is decision-relevant, but not that it is decision-specific.

Other examples for such "neuronal markers" in monkey electrophysiology studies have been provided by Shadlen and colleagues for area LIP, but also for the frontal eye field and the superior colliculus (for references and their discussion, see Chapter 1.6). Most of these pieces of evidence rely on the high spatial and temporal resolution of single-cell recordings. Neurons are typically selected based on their response properties, for example their response in a memory-guided saccade task (Colby et al., 1996). Typically the eye-movement target is then placed in the receptive field of the neuron (Shadlen and Newsome, 2001). Both the average firing rate as well as the time-course can be used to predict when the monkey is going to make a decision.

The processes described in these experiments qualify as decision-specific, because they carry a specific representation of a DV. This already is quite a remarkable achievement, with many pieces of evidence corroborating the existence of a DV in LIP (see the list in Chapter 1.6). However, what could not be demonstrated was that these processes were decision-implementing, because a DV could be formed somewhere else in the brain and fed into area LIP as a signal coding response selection or other cognitive processes. Indeed, with the current methodology available to monkey electrophysiologists, it would be quite demanding to demonstrate decision-implementing processes. After having identified and recorded from all brain regions that carry a DV, it would have to be shown that this particular region is the *first* to carry the representation of a DV ("first implementation"), or that it is not influenced by other brain regions carrying a DV earlier in time ("independent implementation").[11] Since these regions are unknown a priori, the use of neuroimaging could complement the identification of candidate regions for the representation of the DV, and the

[11] To complicate the issue, a causal link to behavior would have to be demonstrated, too. Unlikely as it may be, the existence of a DV somewhere in the brain could be epiphenomenal, i.e. serve no purpose. A complete understanding of the decision-implementing neuronal populations would in that respect only exist when all steps of neuronal transformation from stimulus representation to execution of the decision are understood.

connectivity profile between these regions could serve as an index for their causal relationship.

2.4. The problem of identifying decision-related brain signals with human neuroimaging

Finding neuronal markers is in some way much more difficult in experiments employing functional neuroimaging rather than monkey electrophysiology, which has to do with the much lower specificity of the signal that is investigated. Although the first step of selecting relevant neurons with the desired response properties is avoided in functional neuroimaging studies that can acquire signals from many locations of the brain at the same time, there are two major disadvantages of this technique: the much lower temporal resolution in the range of seconds rather than milliseconds, and the much lower spatial resolution in the range of hundreds of thousands of neurons rather than individual neurons. Both of these problems lead to this low specificity of the signal investigated and make the inferential problem – the problem of finding neuronal markers of decision-related processes – much more demanding.

The low temporal resolution leads to two problems: First, it is difficult to attribute a specific brain signal to a given time point of the decision, which makes it more difficult to distinguish decision-specific processes from decision-unspecific processes. The DV could possibly be disambiguated from other non-specific brain signals by tracking the evolution of this signal in time and matching it to the time-point of the choice, but this would require a much higher temporal resolution not possible with BOLD fMRI. Second, BOLD fMRI cannot easily distinguish constant neuronal responses, e.g. those representing sensory evidence, from time-varying responses, e.g. those reflecting the DV. This is because the BOLD response can be described as a convolution of the underlying neuronal signals with a slow hemodynamic response function. This convolution mimics an averaging or summing of neuronal responses over time and reduces or eliminates the difference between steady vs. increasing neuronal responses. Non-invasive electrophysiological techniques with higher

temporal resolution – electroencephalography (EEG) and magnetencephalography (MEG) – are on the other hand even more limited in their spatial resolution, and the measured brain signals often consist of a spatial mixture of many different processes occurring simultaneously in many different brain regions (for different "unmixing" approaches, see Philiastides et al., 2006; Donner et al., 2009).

The low spatial resolution of fMRI – albeit higher than that of EEG or MEG – leads to two additional problems: First, within a given voxel the signals representing the DV for opposing alternatives might cancel each other out: According to a drift-diffusion process, some neuronal populations responsive to a particular choice alternative would show an increase in activity with evidence for this alternative, while the populations coding the other alternative would show a decrease. This can lead to an overall null-response in the voxel, but in case of asymmetric responses or asymmetries in the number of choice-selective neurons in that voxel to an overall increase or decrease in the measured response. Second, many other processes that are not decision-specific are present around the time of the decision and will more easily be confused with decision-specific processes. They might be decision-related, for example attentional processes that aid the decision-making process, but could also be unrelated processes that co-occur in time, such as processes related to the motor response itself. Decision-relevant, decision-specific or decision-implementing processes are in turn even more difficult to demonstrate, because the measured response can hardly be used to predict the choice of the subject.

2.5. Previous approaches to identifying decision-related brain signals with human fMRI

The difficulties described above have been approached in a number of clever experiments in the attempt to identify neuronal markers of decision-specific processes with fMRI. Here we provide a selected number of approaches representative of the imaging literature on

perceptual decision-making. Some articles reported used several of these criteria to identify decision-related signals:

(a) Correlation of BOLD response and stimulus difficulty (Heekeren et al., 2004, 2006; Pleger et al., 2006; Tosoni et al., 2008; Ho et al., 2009; Noppeney et al., 2010; Kayser et al., 2010a, 2010b; Kovács et al., 2010; Liu and Pleskac, 2011; Erickson and Kayser, 2013)
(b) Correlation of BOLD response and choice reaction time (Binder et al., 2004; Thielscher and Pessoa, 2007; McKeeff and Tong, 2007; Noppeney et al., 2010; Ruff et al., 2010; Kayser et al., 2010a)
(c) Correlation of BOLD response and performance (Lewandowska et al., 2010; Kayser et al., 2010a)
(d) Overall positive BOLD response during task execution (Tosoni et al., 2008; Ho et al., 2009; Kayser et al., 2010a, 2010b; Erickson and Kayser, 2013; Filimon et al., 2013)
(e) Choice probabilities from BOLD response (Pessoa and Padmala, 2005, 2007)
(f) Gradual BOLD increase in slow decision-making task (Ploran et al., 2007, 2011)
(g) Comparison of BOLD signal with predicted signal from cognitive models (Ho et al., 2009; Domenech and Dreher, 2010)
(h) Choice-predictive brain signals using MVPA (Pessoa and Padmala, 2007; Serences and Boynton, 2007; Li et al., 2009; Hebart et al., 2012)

Of all these approaches, the correlation of BOLD response and stimulus difficulty is the most common and also often the primary indicator of a decision-related brain signal, rather than for example an overall positive BOLD response which is often used as an additional criterion. Each of these approaches should reveal brain regions in which the BOLD response is consistent with the representation of a DV. However, are they sufficient to make the inference that indeed a region representing the accumulation of evidence was found, as depicted in Figure 3? Or are they unable to reduce the number of possible alternative

explanations to a sufficient degree? For example, the correlation of BOLD response with RT alone could also indicate regions reflecting top-down attention, response selection, response conflict, categorization uncertainty or the motor response itself (Corbetta and Shulman, 2002; Pessoa et al., 2003; Ridderinkhof et al., 2004; Grinband et al., 2006). Regions correlating with performance alone could also reflect stimulus-processing, representation of sensory evidence, or top-down attention. Since accuracy and RT are often correlated, each approach alone will probably fail to even narrow down the possible candidates. But even the combination of most approaches will at most help finding decision-related brain signals rather than the more specific signals reflecting the DV.

Not surprisingly, a large number of brain regions have been identified as being decision-related, mainly in the posterior parietal and the frontal lobes as well as the insular cortex. While it is possible that much of the brain is devoted to the accumulation of sensory evidence, together the level of specificity of these finding is quite low. In addition – as we will see – these findings can also reveal conflicting results.

2.6 An example approach: Correlations between the BOLD response and stimulus difficulty

We will illustrate the problem of finding decision-specific signals using the most common approach: the correlation of stimulus difficulty and BOLD signal amplitude. According to an evidence accumulation framework (Ratcliff, 1978; Usher and McClelland, 2001) and assuming an asymmetry of responses with stronger responses to positive evidence (Chapter 2.4), the average neuronal signal in an accumulator region at a given point in time should increase with an increasing amount of sensory evidence available to the observer (Figure 5 left). In other words, the more sensory evidence is available, the larger the slope of the accumulated evidence and the faster the accumulation threshold is reached. This time course of the neuronal signal is not observed directly, but is reflected in the measured BOLD signal amplitude. Due to the slow temporal unfolding of this signal, the BOLD response will

not reflect the neuronal signal at a given time point, but rather the integral of the neuronal activity over a period of seconds (in other words the area under the response curve), plotted against time (Figure 5 left). This leads to opposite predictions depending on whether the experimenter uses an *interrogation protocol* in which he himself controls the decision time, or a *free response protocol* in which the decision time is controlled by the subject (Bogacz et al., 2006).

In the *interrogation protocol*, the stimulus is presented for a fixed duration, often followed by a delay, before the response is prompted. The optimal strategy is to accumulate all information until the stimulus is terminated and to maintain this accumulated evidence until a response can be executed.[12] Since the integral of the accumulated evidence across time – which is reflected in the BOLD signal amplitude – increases with the amount of accumulated evidence, the BOLD signal is *positively* related to the average amount of sensory evidence available (Figure 5, top right).

[12] Whether evidence is accumulated to a bound as depicted in Figure 5 (Shadlen and Newsome, 2001; Kiani et al., 2008) or continues to be accumulated does not change this prediction.

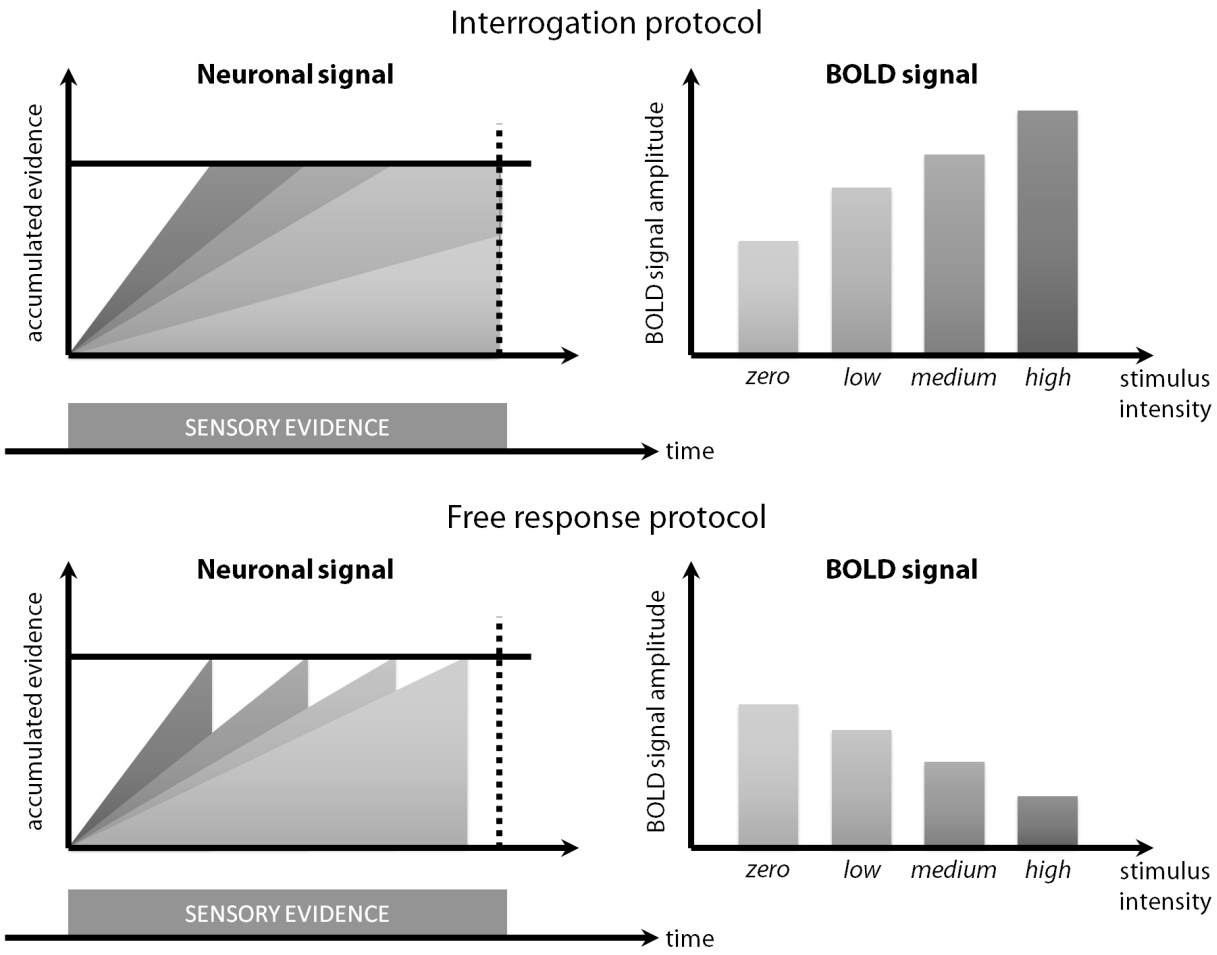

Figure 5 Predictions of neuronal signal (left) and related BOLD signal amplitude (right), depending on the amount of sensory evidence shown and based on the interrogation protocol (top) and the free response protocol (bottom).

In the *free response* protocol, the stimulus duration depends on the RT of the observer, because the observer responds as soon as the accumulated evidence has reached a hypothetical "decision bound" (Bogacz et al., 2006; Gold and Shadlen, 2007). For higher levels of sensory evidence, the accumulated signal is thus present for a shorter period of time. From this follows that the area under the response curve is smaller for faster decisions. Counterintuitively, this leads to a BOLD signal that is *negatively* related to the average amount of sensory evidence, or in other words to a decreasing BOLD signal amplitude with increases in sensory evidence (Figure 5, bottom right).

Indeed, most studies are in agreement with this suggested relationship: They either used an interrogation protocol and focused on a *positive* relationship between sensory

evidence and BOLD signal amplitude (Heekeren et al., 2004, 2006; Pleger et al., 2006; Tosoni et al., 2008; Kovács et al., 2010); or they employed a free response protocol and focused on a *negative* relationship between the two (Ho et al., 2009; Noppeney et al., 2010; Kayser et al., 2010a, 2010b). Two studies were inconsistent with the expected relationship, in that they used an interrogation protocol, but focused on a negative relationship. One of these studies did not justify this choice (Erickson and Kayser, 2013), while the other explained it by the unknown time courses of maintenance of accumulated evidence (Liu and Pleskac, 2011); however, this explanation would necessitate a complex time-dependent recoding of accumulated evidence into a different format.

The studies using a positive relationship typically report brain regions as decision-related that *disengage* when a task is performed, while the studies using a negative relationship typically focused on regions that *engage* when a task is performed; the regions found are also known as task-negative and task-positive networks, respectively (Fox et al., 2005; Buckner et al., 2008). For the positive relationship, it has already been suggested that such brain signals may *only* reflect a disengagement from this task-negative network (Singh and Fawcett, 2008; Tosoni et al., 2008), because most often they lead to a negative overall BOLD response. This disengagement may be stronger for more difficult tasks, i.e. where sensory evidence is lower, and would lead to a positive relationship between the amount of sensory evidence and the BOLD response. The results using a negative relationship could, on the other hand, be related to different levels of attention, decision-evaluation, or performance monitoring, but also to varying degrees of difficulty in response selection or a number of other cognitive processes (Corbetta and Shulman, 2002; Pessoa et al., 2003; Ridderinkhof et al., 2004). Potentially, these processes may be decision-related because they modulate the decision process, but they are not decision-specific because the decision could be computed without them.

2.7 Empirical findings on the correlations between the BOLD response and stimulus difficulty

Together, these studies make an important prediction: If the relationship of stimulus difficulty and BOLD signal amplitude is a useful index, then together the results of all studies reporting this relationship should indicate candidates for a region more generally involved in decision-making. Indeed, this would be a quite useful marker, because such a region would show a dependence that would be difficult to explain by mechanisms other than evidence accumulation. On the other hand, regions that are inconsistent with this idea, i.e. regions that show a positive or a negative relationship irrespective of the experimental protocol, could still possibly represent the DV. However, this representation would not be generally observable, but masked by a different cognitive process that always shows a positive or a negative relationship with stimulus difficulty.

For the purpose of this comparison, we compiled the peaks of the results of studies that reported positive or negative correlations of BOLD signal with sensory evidence. To narrow down the focus for better comparability of results, we only included studies using unemotional visual stimulation. In addition, we only included studies for which statistics had been carried out in MNI space; otherwise we could not relate these studies to another. In total, eleven studies were selected (Table 1), some of which did not use the correlation of BOLD response and sensory evidence for the definition of decision-related signals (Bankó et al., 2011; Hebart et al., 2012), and one which even was not investigating perceptual decision-making per se (Singh and Fawcett, 2008). Six of these studies were carried out with an interrogation protocol (focus on behavioral accuracy), and five studies used a free response protocol (focus on both accuracy and RT). We generated maps from the results tables of the studies that were specific to the visual task and the variation of stimulus difficulty by plotting colored circles at the corresponding locations of the brain, projected to the cortical surface.[13]

[13] We are grateful to Annalisa Tosoni and Andrew Kayser for sharing with us the exact coordinates and statistics of their studies that had only been depicted in figures (Tosoni et al., 2008; Kayser et al., 2010a).

Study	Task	Number of categories	Response modalities	Protocol	Stimulus duration	Response possible before stimulus offset?
Heekeren et al (2004)	face-house in spatial-frequency noise discrimination	two	manual	interrogation	1.0 s	no
Heekeren et al (2006)	random dot motion	two	manual / saccade (cue-dependent)	interrogation	1.0 s	not reported
Singh and Fawcett (2008)	random dot motion	two	manual	interrogation	1.0 s	no
Tosoni et al (2008)	face-place in white noise	two	manual / saccade	interrogation	0.30 s	no
Ho et al (2009)	dual random dot motion (cue-dependent)	four	manual / saccade (different runs)	free response	1.5 s	yes
Kayser et al (2010a)	random dot motion	two	manual	free response	2.5 s	yes (forced)
Kayser et al (2010b)	random dot motion OR color proportion (cue-dependent)	two	manual	free response	2.5 s	yes (forced)
Kovács et al (2010)	motion in depth	two	manual	interrogation	6.0 s	no
Noppeney et al (2010)	object discrimination	two	manual	free response	2.0 s	yes (forced)
Bankó et al (2011)	face gender discrimination	two	manual	free response	0.25 s	no
Hebart et al (2012)	random dot motion	two	manual	interrogation	1.5 s	no

Table 1 Studies selected for the comparison of BOLD signal correlations across response protocols (interrogation vs. free response protocol).

The results of this comparison are shown in Figure 6. In Figure 6A, results are plotted separately for positive and negative correlations between BOLD signal amplitude and sensory evidence. As can be seen, positive and negative slopes do not overlap, but form largely separate clusters. Clusters for positive slopes can loosely be grouped around the left superior frontal sulcus, the left angular gyrus, the precuneus, and possibly around the medial prefrontal cortex. For negative slopes, such clusters can be identified around the supplementary motor area, the anterior cingulate cortex, anterior insula, inferior frontal gyrus, premotor cortex, intraparietal sulcus, visual cortex, and thalamus. The absence of any overlap in these clusters means that among the studies selected for this comparison, there was no region in which the correlation reversed depending on the task protocol. These

results do not support the assumption that increases or decreases in BOLD signal with sensory evidence can be used to indicate accumulation of sensory evidence.

Figure 6B shows the same peaks, but this time sorted depending on whether results would be consistent or inconsistent with the assumption that a positive slope reflects accumulation in tasks with an interrogation protocol and that a negative slope reflects accumulation in tasks with a free response protocol. Following this logic, a correlation of sensory evidence with the BOLD signal amplitude should not be used unambiguously to indicate evidence accumulation in those brain regions exhibiting inconsistent patterns. These results could also be attributed to processes other than evidence accumulation. Of the clusters reported above, the supplementary motor area and anterior cingulate cortex, the anterior insula, inferior frontal gyrus, premotor cortex and thalamus include patterns inconsistent with the above assumption. On the other hand, the superior frontal sulcus, the angular gyrus, precuneus, medial prefrontal cortex, intraparietal sulcus and visual cortex all exhibit largely (though not entirely) consistent patterns. The correlation of BOLD signal and sensory evidence in any of these regions could still be used to limit the regions reflecting sensory evidence accumulation. However, because none of these regions showed a reversal in response for positive and negative correlations (see Figure 6A), this means that these candidate regions were only found either in tasks using an interrogation protocol or in tasks with a free response protocol, but not in both. If one assumes a generality of an accumulator region across both types of tasks, then current evidence does not support that any of these signals identified an accumulator region.

From these illustrative analyses we conclude that the use of correlations of BOLD signal and sensory evidence did not reveal any consistent patterns across both types of task protocols that could be used to identify brain regions participating in the accumulation of sensory evidence. In addition, following the logic applied above, a number of brain regions even showed responses that are inconsistent with this functional role. These conclusions of course crucially depend on the assumption that decision-related BOLD responses should

increase with sensory evidence in tasks with an interrogation protocol, and decrease in tasks with a free response protocol. However, this assumption does not need to be true.

First, the conclusions depend entirely on the speed with which accumulation occurs. When accumulation is fast, any subtle differences in the BOLD signal across levels of sensory evidence might disappear. This, however, would invalidate the method of using BOLD correlations with sensory evidence altogether, i.e. the premise of this analysis, which was not tested in the present study, but taken for granted, just as was done in other studies. Second, the speed-accuracy tradeoff is different between the tasks, i.e. the threshold may in fact be lower in the free response protocol than the interrogation protocol, leading to different overall levels of brain activity depending on the amount of accumulated evidence. While this makes a direct comparison within one study challenging, this should only affect the overall slope of the response across different levels of sensory evidence, but not the sign of the slope. Third, it is possible that accumulation always occurs only until a threshold is reached, after which the signal in that region returns to baseline (Liu and Pleskac, 2011). This should lead to a negative relationship of BOLD signal both for both types of response protocols. In that case, information would have to be maintained in another brain region; otherwise the subject could not respond after a delay. However, this is at odds with neurophysiological results demonstrating that neuronal activity remains high until a response is executed (Shadlen and Newsome, 2001). Fourth, subjects may continue to accumulate information even when the response has been carried out – or more generally – the accumulation process may not follow the expected patterns. Again, this disagrees with neurophysiological findings (Shadlen and Newsome, 2001; Roitman and Shadlen, 2002) and also disagrees with the premise for carrying out this type of correlation, not with the conclusions drawn from this comparison of studies.

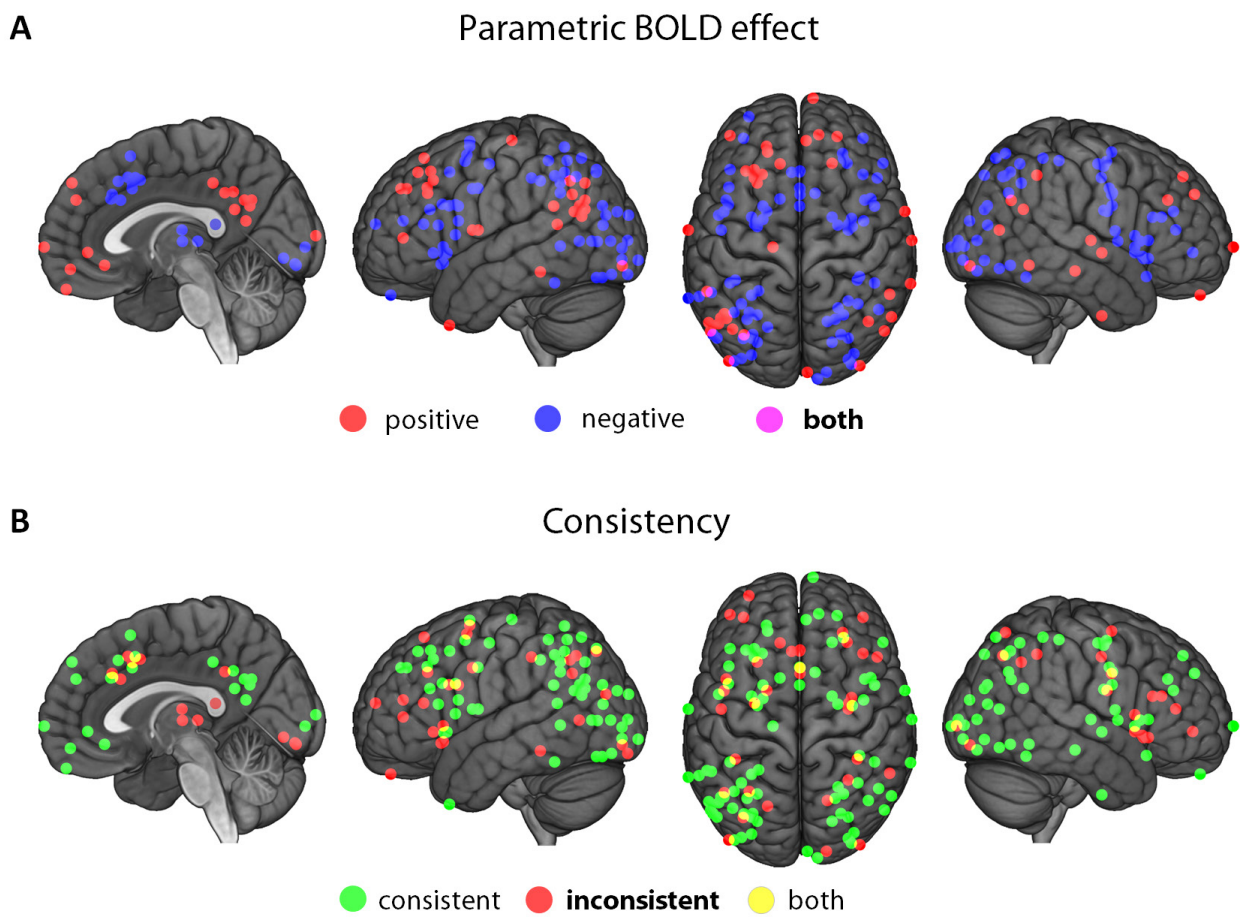

Figure 6 **Peaks of reported results of studies showing correlations of BOLD signal and sensory evidence in the visual modality. The results are depicted from medial and lateral views from the side and from the top. Results in between layers, e.g. from the anterior insula, are projected to the surface.** ***(A)*** **Results are grouped in positive (red) and negative (blue) correlations of BOLD signal with sensory evidence, independent of the response protocol used. There is no overlap between red and blue dots, demonstrating that no brain region shows a reversal across interrogation and free response protocols.** ***(B)*** **Results are grouped in consistent (green: speeded and negative correlations, unspeeded and positive correlations) and inconsistent responses (red: speeded and positive correlations, unspeeded and negative correlations). Inconsistent responses provide evidence against a specific involvement of this brain region in perceptual decision-making.**

Taken together, these illustrations show that any assumptions made about the relationship between BOLD signal amplitude and sensory evidence accumulation do not generalize across tasks. This either means that the correlation between BOLD signal amplitude and sensory evidence is not a good neuronal "marker", or that the results of the studies above are in fact not comparable. For example, some tasks were carried out using manual responses while others were using saccades. Nonetheless, it is still a matter of debate whether evidence accumulation occurs in a response modality-specific or response modality-general manner, i.e. whether there is a general decision-making process

independent of the motor effector (Heekeren et al., 2006; Tosoni et al., 2008; Ho et al., 2009; Bennur and Gold, 2011; Liu and Pleskac, 2011; Rahnev et al., 2011; Hebart et al., 2012; O'Connell et al., 2012; Filimon et al., 2013). In addition, it is possible that the accumulation process depends on the type of stimulus used (Liu and Pleskac, 2011), i.e. for example that the accumulation of evidence about faces vs. houses is computed differently than evidence accumulation about motion direction, or even that evidence is accumulated differently for different types of motion coherence or stimulus duration. Finally, it is possible that depending on speed or accuracy emphasis, different regions are used to accumulate sensory evidence (Wenzlaff et al., 2011). This idea is consistent with the recent finding that the duration of evidence accumulation can be adjusted to the task demands (Ossmy et al., 2013). The inconsistency demonstrated above may be related to one or several of these paradigm-specific effects. Since most studies are aimed at making conclusions that generalize beyond the paradigm to more universal mechanisms, the questions about modality, stimulus, and speed-accuracy specificity are important questions that require further investigation.

2.8 Possible solutions to the problem of low functional specificity of fMRI signals

The problems illustrated in the previous section are a direct consequence of the low functional specificity of the BOLD signal, both in terms of temporal and spatial resolution (see Chapter 2.4). Were the specificity higher in the temporal domain, then the time course of neuronal signals could be used to distinguish evidence accumulation from other unspecific signals which follow a different time course of activity. Were the specificity higher in the spatial domain, then it would be possible to track evidence accumulation for one choice, but not the other (i.e. the accumulation of evidence for choice A, rather than a mixture of all possible choices); in that case the processes related to the accumulation of sensory evidence could be distinguished from other unspecific processes.

One approach to overcome the limit in time resolution has been to extend the duration of the accumulation process and look for gradual increases in BOLD responses

(Ploran et al., 2007, 2011) rather than steady responses that would rather reflect unspecific processes such as attention, or responses that show a marked increase which probably reflect choice-related processes and those following the choice. Other studies introduced a time between stimulus presentation and response execution to distinguish motor responses from evidence accumulation (Tosoni et al., 2008; Liu and Pleskac, 2011; Erickson and Kayser, 2013). While these approaches are promising, it also means that sensory evidence must be revealed very gradually or that motor responses need to be delayed by several seconds, which makes it possible that in this case evidence is accumulated quite differently and possibly stored in different regions of the brain than when accumulation and response happen within a second or two (Gold and Shadlen, 2007). In addition, changes of mind may exert a stronger effect for longer delays which would lead to different signals of sensory evidence representation during stimulus encoding than during response execution (Resulaj et al., 2009; Bollimunta et al., 2012; Fleming and Dolan, 2012). A possible extension to these studies would be a revelation of sensory evidence that varies across time, i.e. making the stimulus either more difficult or easier across time. This could introduce a jitter in the task difficulty across time, while evidence is accumulated rather continuously, and could be used to distinguish unspecific responses that vary with task difficulty from more decision-specific signals.

As an alternative to investigating overall changes in the BOLD signal, MVPA can be carried out to directly reveal decision-specific brain signals (Haynes et al., 2007). This method can be used find patterns of brain activity that distinguish between two specific choices, for example whether the subject chose upward vs. downward motion. MVPA has been applied in the field of perceptual decision-making using both region of interest-based methods (Pessoa and Padmala, 2007; Serences and Boynton, 2007) as well as “searchlight methods” (Li et al., 2009; Hebart et al., 2012), an approach which reveals the amount of information in local brain activity patterns across the whole brain (Kriegeskorte et al., 2006; Haynes et al., 2007).

For a valid interpretation of results it is, however, important to carefully control for different aspects of the task. For example, the stimulus itself might be strongly correlated with the choice of the subject. This problem has been approached in a clever study by Li et al. (2009) where the categorical bound was changed, but the stimulus remained the same. Alternatively, this problem can be advanced by calculating classification outcomes for choices separately for all stimuli: Choice-specific information could be estimated for all different stimulus categories separately, thus revealing patterns of brain activity independent of the stimulus shown on the screen. This method is analogous to the calculation of choice probabilities (Britten et al., 1996) and is particularly well suited for stimuli close to the perceptual threshold, because there will be a sufficient number of choices for both categories. However, it is still difficult to distinguish the representation of sensory evidence alone from signals representing the accumulated evidence using MVPA, which can be seen as the major shortcoming of this method.

In addition, the choice itself may correlate with specific motor responses, revealing choice-specific patterns of activity in motor response and motor preparation-related brain regions. While this problem can be reduced by long time intervals between choice and motor response, alternatively a response-mapping screen can be used to decouple choices and motor responses (Hebart et al., 2012). However, if the choice is encoded in motor preparation-related brain regions, such a response may be missed by this approach, because choices and motor responses may overlap in time which may annihilate the patterns used to classify choices. When taking care of these potential shortcomings, MVPA may actually prove to be a valuable step towards revealing brain regions that are decision-specific.

3. Summary and discussion of empirical studies

We discussed in detail Chapter 2 that in contrast to monkey electrophysiology most current functional neuroimaging studies in the field of perceptual decision-making suffer from low functional specificity. This was supported both on theoretical grounds (Chapters 2.4 and 2.5) as well as empirically by a comparison of recent studies that varied the difficulty of perceptual tasks (Chapters 2.6 and 2.7). We concluded that the problem of low functional specificity can be addressed by using MVPA on patterns of brain activity in fMRI (Chapter 2.8). This is the approach taken in the empirical work presented in this dissertation. In the following sections, the three studies used to investigate perceptual decision-making and related neuronal processes are briefly summarized. The first study investigates the representation of perceptual choices when movements cannot be planned in advance. The second study takes a closer look at the relationship of decision variables and perceptual confidence. The third and final study investigates possible mechanisms of temporary storage of perceptual information which can only be reported after an extended delay.

3.1 Study 1: The representation of perceptual choices independent of motor plans

There are two competing frameworks of how perceptual decisions are represented in the brain. One framework assumes that perceptual decisions are encoded as choices among several competing stimulus interpretations, while the other assumes that decisions are reflected as choices between multiple actions. In the former framework, perceptual decisions are only the consequence of the act of categorizing, or more generally of interpreting the incoming sensory information (Baars, 1983; Dehaene and Naccache, 2001); here the interpretation of sensory information is relayed to motor structures that later are used to execute the choice. In the other framework, incoming sensory information is related to the intention of an agent to execute a response (O'Regan and Noë, 2001; Cisek, 2007; Shadlen et al., 2008; Freedman and Assad, 2011). If the agent knows about the possible courses of

actions depending on the stimulus properties, then the incoming stimulus information is mapped directly to brain regions involved in motor planning. In other words, the interpretation of sensory evidence takes place in a format that is already mapped to the motor intention afforded by the incoming sensory information.[14]

Monkey electrophysiology studies indicate that it is possible to accumulate sensory evidence in form of an intention to act, i.e. as a motor plan. The reason for this is that they find signatures of evidence accumulation in brain regions that are thought to be related to planning and initiating a motor response (Horwitz and Newsome, 1999, 2001; Gold and Shadlen, 2000, 2003; Hernández et al., 2000; Shadlen and Newsome, 2001; Roitman and Shadlen, 2002; Romo et al., 2004; Hanks et al., 2006; Churchland et al., 2008; Kiani and Shadlen, 2009; Bollimunta et al., 2012). Although these results revealed many features of the alleged accumulation process, the generality of these results in terms of decision-making is still disputed. Indeed, it is possible that evidence is accumulated in an abstract format and only relayed to brain regions representing motor plans when the appropriate motor response is known in advance. Human neuroimaging would be invaluable for identifying candidates for such brain regions, which could later be investigated in more detail with monkey electrophysiology. A number of human neuroimaging studies used multiple response effectors to identify brain regions that respond irrespective of the motor response (Heekeren et al., 2006; Tosoni et al., 2008; Ho et al., 2009; Liu and Pleskac, 2011). They reported conflicting results, with some supporting the notion of abstract accumulation (Heekeren et al., 2006; Ho et al., 2009; Liu and Pleskac, 2011) – albeit all with different candidate regions – while others found no such evidence (Tosoni et al., 2008).

An alternative way of investigating whether decisions are represented in an abstract format is to reveal the set of possible motor responses to the subject only after the stimulus has been shown. Using this approach, monkey electrophysiology studies reported a

[14] A possible challenge for the second framework is the existence of abstract decisions, where the response modality is unknown in advance. However, the sensory information could be translated into structures that encode not a motor plan per se, but into structures encoding a rule (Shadlen et al., 2008): “If another stimulus X occurs which signals the necessary response Y, then carry out response Y, otherwise carry out response Z.”

representation of abstract decisions in dlPFC (Gold and Shadlen, 2001), as well as the superior colliculus (Horwitz et al., 2004). However, these studies only found a small number of cells responding irrespective of the goal of the choice, and the results in the superior colliculus could also reflect a spatial response rather than the perceptual decision. Stronger evidence was provided more recently by recordings in monkey LIP (Bennur and Gold, 2011). This study reported the accumulation of sensory evidence, the encoding of a response rule and the saccadic motor response, all multiplexed within the same neurons. However, this study focused on a single brain region in the macaque, and it is unclear whether other brain regions represent decisions in an abstract format and if these results generalize to decisions not reflecting a saccadic response.

In our first study (Hebart et al., 2012) we investigated the representation of perceptual choices about motion direction independent of motor plans in humans, using a design in which the association of motor response (left or right button press) was revealed to the subject only after the stimulus had been shown. This design effectively prevented the accumulation of evidence in a motor format. We used MVPA in a searchlight approach (Kriegeskorte et al., 2006; Haynes et al., 2007) to search throughout the entire brain for local patterns of brain activity informative about the choice of subject. In addition, we varied the amount of sensory evidence available to the observer. This allowed us to address another question: How are perceptual choices represented depending on the amount of sensory evidence available to the observer? The amount of information about choices buried in local patterns of activity should increase with increasing sensory evidence available. Other than the mean BOLD signal, this result can be interpreted meaningfully as being specific to the choice of the subject. In a second step we could then investigate the shape of this effect across levels of sensory evidence. A region related to sensory evidence and evidence accumulation should show increases in information with increasing sensory evidence. However, this approach could also reveal other patterns. For example, subjects could adapt their accumulation to the demands of the task, as has been suggested earlier (Philiastides et al., 2006; Philiastides and Sajda, 2007). Indeed, if the task is very simple, then subjects

could directly read-out information from those brain regions representing sensory evidence and only resort to separate evidence accumulation when it is afforded by the task demands.

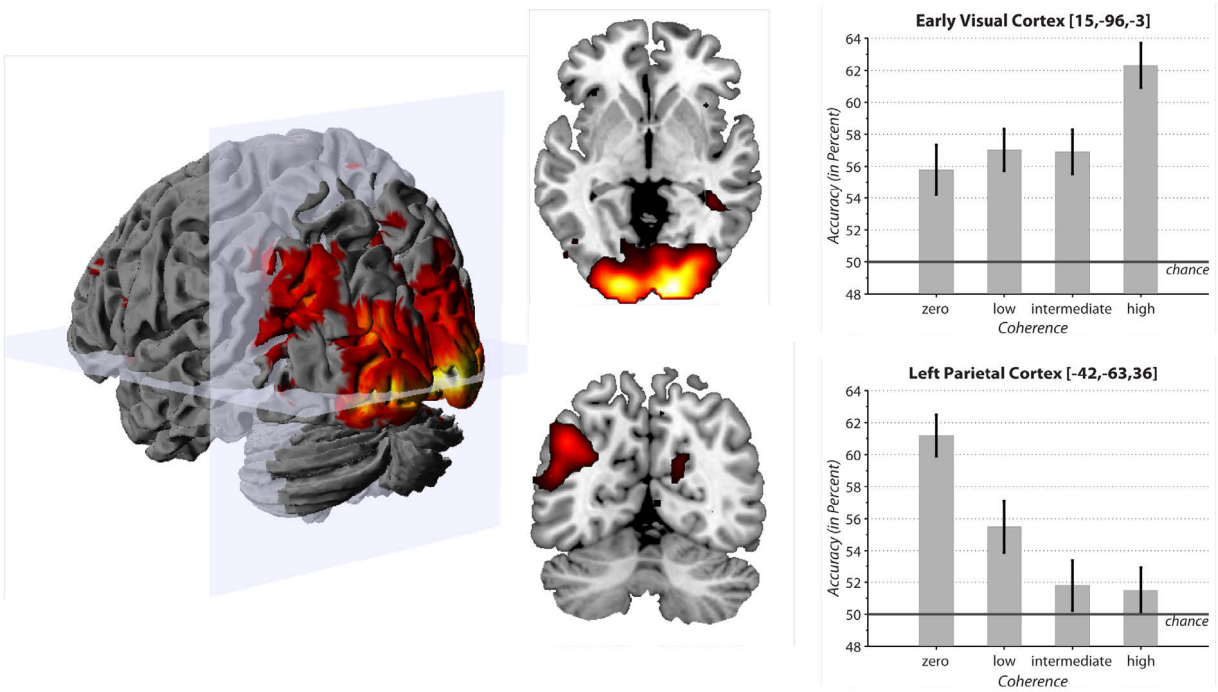

Figure 7: Results of Study 1, using multivariate pattern analysis in a searchlight framework. Both early visual and left posterior parietal cortex carried information about the choice of the subject. While information in early visual cortex was above chance even for zero motion coherence and increased with increasing levels of coherence, information in left posterior parietal cortex decreased with increasing motion coherence.

The main results of this study are threefold (Figure 7). First, we found that both early visual and left posterior parietal cortex represented subjects' choices independent of motor plans. Second, even at zero motion coherence early visual cortex was found to carry information about the choice of the subject. Third, while information in early visual cortex increased with motion coherence, the reverse pattern was found in left posterior parietal cortex: The easier the decision was, the smaller the amount of information about the choice in this brain region. The increase in sensory evidence mirrored in early visual cortex is in line with an increasing subjective representation of the perceptual motion signals even at an early stage of visual processing, rather than reflecting only the stimulus presented on the screen (Ress et al., 2000; Ress and Heeger, 2003). On the other hand, decreases of information in left posterior parietal cortex point towards a separate mechanism of decision-making that is

most informative when choices are difficult. This could reflect an adaptive accumulation mechanism that only comes into play when evidence is weak. When a lot of sensory evidence is available, the subjects could determine the choice from signals in those regions representing sensory evidence (Uchida et al., 2006). Alternatively, this signal could refer to the read-out the representation of the criterion of the subject, which has a particularly strong influence at lower motion coherences since in the absence of meaningful sensory input the choice should on average be determined by the criterion of the subject (Hanks et al., 2011).

Taken together, our results show for the first time unambiguously the representation of perceptual decisions without motor plans in humans. Both early visual and left posterior parietal cortex contribute to perceptual decisions, but differently depending on the amount of sensory evidence. This finding points towards more flexible decision-making processes than has previously been assumed. In addition, the left posterior parietal cortex can serve as a region that carries a more abstract format of perceptual decisions of motion. It remains to be seen if this result generalizes to other forms of perceptual decision-making. Although speculative, it is possible that accumulation of evidence happens in or near those sensory brain regions that encode the stimuli. For example, auditory stimuli could lead to evidence accumulation in or around auditory cortex. Recently, it has been shown that working memory storage takes place in early visual cortex and that both visual stimuli and working memory traces have similar neuronal patterns (Harrison and Tong, 2009). This demonstrates the capacity to store information in the same regions where new information enters in. According to this idea, only when evidence cannot be accumulated in a sensory format, a re-distribution to higher-level brain regions becomes necessary (Bennur and Gold, 2011). When the appropriate motor response is known in advance, this signal is relayed directly to motor structures. This relaying of information would constitute an evolutionary advantage, because it allows the observer to respond as soon as enough evidence has been accumulated, rather than having to wait for motor preparation until sufficient evidence has been accumulated (Shadlen et al., 2008).

3.2 Study 2: The relationship between perceptual decision variables and confidence

Perceptual decisions most often result in discrete choices, such as whether or not a radiologist diagnoses some tissue to be malignant or benign. These discrete choices are thought to be based on integrated evidence that is available to the senses, for example the local intensity of a CT image. People seem to have access to the quality of information driving their choices, because they can report their certainty in their choices. This ability to report the amount of perceptual information that is guiding our choices is known as perceptual confidence. Confidence enables observers to correctly predict the consequences of their own decisions in a more fine-grained manner as would be possible by making use only of their choices. It allows them to choose a compromise between multiple response alternatives when available. It can be used to justify choices to others and to weigh one's own evidence against that of other people. But confidence can also serve as a learning signal: Instead of using discrete choices and comparing them against the outcome of a decision, observers can update their predictions about the world more precisely and learn from violations of their predictions. By using their knowledge about the probability of states in the environment, confidence can also serve as an internally generated feedback signal.

Previous animal electrophysiology investigations of confidence have shown that a confidence signal can be found in the orbitofrontal cortex of rats (Kepecs et al., 2008), and a signal related to the DV in macaque LIP has been found to predict when a monkey was going to opt out on a difficult decision, in other words reflecting the confidence of the monkey in that decision (Kiani and Shadlen, 2009). How confidence is computed in the human brain has remained poorly understood. Confidence most often shows a strong positive correlation with the correctness of decisions (Peirce and Jastrow, 1884) and – when the subject controls the speed of response – a negative correlation with RTs (Volkmann, 1934; Reed, 1951). Both accuracy and RT are used in behavioral models that describe perceptual decision-making (see Chapters 1.2 and 1.3), so it is only natural to assume a close relationship of perceptual decision-making and confidence (Vickers, 1979). Signal detection theory (Chapter 1.2) predicts confidence to be a signed form of the unsigned DV: The further away the choice

from the criterion, the higher the confidence of the observer (Green and Swets, 1966; Macmillan and Creelman, 2005). In other words, confidence can be calculated by rectifying the DV (Figure 8).

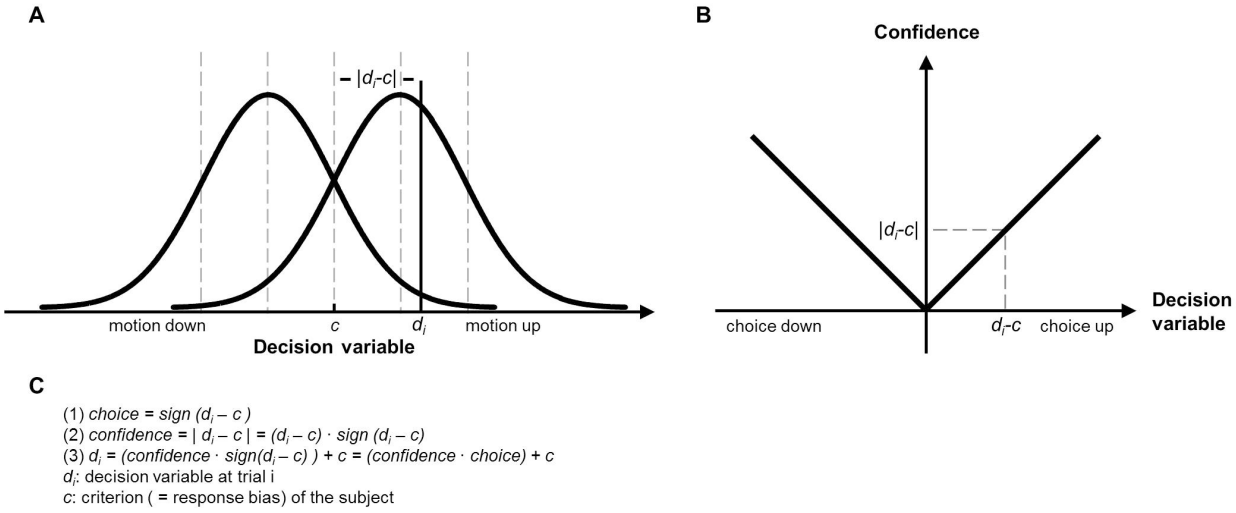

Figure 8. The relationship of the decision variable and of confidence in the signal detection theory framework. *(A)* Confidence is the absolute distance of the decision variable at trial *i* from the criterion *c*. *(B)* The relationship between confidence and the decision variable in a graphical format. The further away the decision variable from the criterion, the higher the confidence. *(C)* The relationship expressed in mathematical format. Formula 3 indicates that the decision variable can be constructed by multiplying the confidence by the choice of the subject.

This simple relationship between these two variables can be used to explore the neuronal representation of the perceptual DV, of confidence, and of their relationship. In our second study (Hebart et al., submitted), we employed a task of fixed difficulty in which we asked subjects to judge the dominant direction of motion in a random dot motion discrimination task. Following their choice, subjects were prompted to indicate the confidence in their judgment. In that way, we could investigate the neuronal underpinnings of perceptual confidence. Importantly, by using the predictions from signal detection theory we inferred the perceptual DV from confidence ratings and choices. We then used this variable to investigate the neuronal representation of the DV, but could in that way also link the DV to confidence.

Perceptual confidence was found to be represented in the BOLD signal amplitude of the ventral striatum around the nucleus accumbens: The more confident a subject was, the higher the activity in this brain region. This region is typically found to be activated in tasks

involving reward, learning, and motivation (Wise, 2004). Activation in this region might reflect the rewarding feeling associated with being confident, which would reinforce the observer to behave in a similar way again (e.g. to pay attention). This is in line with a striatal evaluation signal reported in macaque monkey (Ding and Gold, 2010) and suggests that confidence can serve as a learning signal even in the absence of feedback (Daniel and Pollmann, 2012).

For an unconfounded investigation of the DV, we first controlled for the motion direction presented on the screen by selecting brain regions from which we could decode in a searchlight classification framework choices independent of the presented motion direction (Britten et al., 1996). In the next step, the representation of the DV was investigated using a searchlight analysis in a regression framework, but limited to the regions identified in the first step. Information about the DV was found predominantly in frontal and parietal brain regions (Figure 9). This result is consistent with previous findings regarding the representation of perceptual choices (Li et al., 2009) and of the DV in general (Kim and Shadlen, 1999; Gold and Shadlen, 2000; Shadlen and Newsome, 2001).

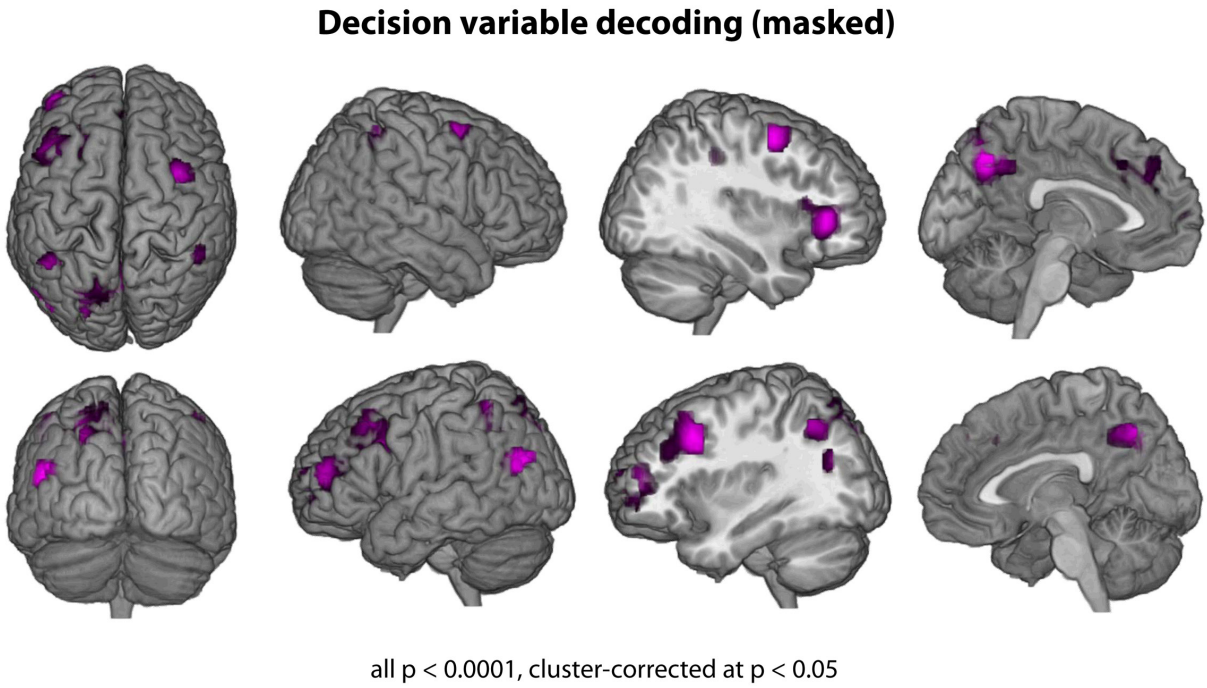

Figure 9 Results of Study 2, showing brain regions carrying information about the decision variable. The ventrolateral prefrontal cortex (top row, third from the left, lower cluster) was found to represent the decision variable in a format that could be used to predict the response of the ventral striatum to perceptual confidence.

In a last step we were interested to find if one or several of these regions exhibited a specific covariation with signals in the ventral striatum. To investigate this, we selected the searchlights around the peaks from the identified regions, took the predicted labels from the DV decoding of these searchlights, and transformed them according to signal detection theory (Figure 8C) to match the representation of confidence in the ventral striatum. This analysis revealed that only the right ventrolateral prefrontal cortex (vlPFC) showed a specific covariation with the ventral striatum as predicted by signal detection theory. The role of the vlPFC is in line with previous applications of MVPA to the decoding of perceptual choices (Pessoa and Padmala, 2007; Li et al., 2009). The finding of this specific covariation suggests a simple mechanism for the "construction" of perceptual confidence: Choice-specific DVs in the vlPFC are pooled and rectified to compute perceptual confidence in the ventral striatum. The bigger the activity levels of *any* of the choice-selective prefrontal populations, the bigger the response of the striatal neurons encoding confidence.

These results provide a better understanding of how confidence could be constructed from DVs. In addition, they provide support for signal detection theory as a model linking perceptual decision-making and confidence. This is because the results suggest a simple and direct transformation between the representation of decisions and confidence in the human brain that is consistent with signal detection theory. According to this approach, the ability of subjects to report their confidence does not need to rely on a separate "confidence"-accumulation process (Busey et al., 2000). Rather, confidence can be seen as the direct result of the DV. However, there are three aspects of confidence that are not explained by this model: First, it has been shown that confidence cannot fully be explained by the DV, but rather that observers vary in their ability to report their confidence (Fleming and Dolan, 2012). However, variability in the ability to report one's confidence could also be explained by noise added to the transformation process of the DV to confidence which might vary between subjects and may depend on other cognitive mechanisms that would be found by investigating this variability between subjects (Fleming et al., 2010, 2012). Second, people often are far too confident or too inconfident in their decisions, reflecting a specific bias in

their confidence reports (Adams and Adams, 1961; Björkman et al., 1993). This criterion shift might relate to their inability to report their confidence appropriately, but is not captured by the direct transformation depicted above. However, assuming that within a given task the relative difference between two ratings is preserved, this is not a problem for the calculation of confidence from the DV or vice versa. In other words, the criterion acts as a constant in the transformation process described above, so only relative confidence is derived from the DV, not the absolute confidence level. Third, signal detection theory is a model that does not make any predictions about RTs, and only recently models have been proposed that combine accuracy, RTs, and confidence judgments (Ratcliff and Starns, 2009; Pleskac and Busemeyer, 2010). In the future, neuroimaging experiments should be carried out that incorporate exactly the relationship of these three variables to get a more complete understanding of the emergence of confidence judgments in the human brain.

3.3 Study 3: The representation of the contents of visual short-term memory in visual and parietal cortex

Visual short-term memory (VSTM) reflects an active representation of perceived or imagined visual information that can be used in ongoing cognitive tasks and that can last for several seconds (Luck, 2007). Not surprisingly, VSTM also plays an important role in perceptual decision-making tasks, which is supported by two pieces of evidence. First, perceptual decision-making tasks often require comparing two successive stimuli, where the first acts as a reference and the second as the judgment stimulus. If the time interval between the two visual stimuli exceeds the critical duration of the short-lived, passive form of memory called “iconic memory” (Sperling, 1960; Landman et al., 2003), this requires an active representation of the first stimulus in VSTM. Most experiments in perceptual decision-making employing this type of comparison are carried out in the tactile domain, where comparisons are made between vibration frequencies (Mountcastle et al., 1990). Interestingly, the same neurons that fire throughout the delay period between both stimuli and reflect the first

stimulus can encode the difference between the two stimuli and thus the DV (Romo et al., 2002). In other words, there might be an overlap between the representation of short-term memory and the DV.

The other piece of evidence comes from perceptual decision-making tasks using interrogation protocols in which the decision can only be carried out after a specific delay that is controlled by the experimenter. Here the subject needs to hold a representation of the decision in memory until a response can be executed. Interestingly, area LIP which has been shown to carry a DV for eye-movement decisions (see Chapter 1.6) is also active in a spatially specific manner when stimuli need to be maintained in VSTM (Constantinidis and Procyk, 2004). In fact, most studies on the role of LIP in perceptual decision-making use a memory-guided saccade task to isolate neurons that might carry a representation of the evolving DV (Colby et al., 1996; but see Meister et al., 2013). These pieces of evidence suggest a close link between VSTM and perceptual decision-making. Indeed, one can easily imagine many real-life situations in which one carries out inter-temporal decisions or in which the perceptual choice needs to be maintained in short-term memory. For that reason, it makes sense that the same neurons that encode perceptual decisions are also used to represent the remembered content of the stimulus.

However, to date very little is known about whether posterior parietal cortex (PPC) in humans is memory content-specific or content-unspecific, i.e. whether it stores information about visual stimuli or whether it merely carries a signal that is used to maintain a representation of the memorized content elsewhere in the brain. An abundance of studies have shown that activity in PPC increases during short-term memory tasks (reviewed in Wager and Smith, 2003) and that the level of activity scales with memory load (Todd and Marois, 2004). However, these findings are in line both with a content-specific and a content-unspecific representational format and alone do not distinguish between these two alternative explanations for the role of PPC in VSTM. Others believe that memory content is re-represented into prefrontal cortex (Goldman-Rakic, 1995; Courtney, 2004; Funahashi, 2006). A third view is that the same neurons encoding visual stimuli contain the architecture

to represent remembered stimuli (Postle, 2006). Harrison and Tong (2009) confirmed this third view recently by showing that already early visual cortex can carry a representation of items held in VSTM, although the mean BOLD signal indicated the absence of a representation in this region. This demonstrated that a re-representation of visual stimuli in parietal or even frontal cortex does not seem to be a necessary requirement. However, the authors focused on visual cortex alone, leaving open if visual memory content is stored elsewhere in the brain. The representation of perceptual DVs in a memory format in parietal cortex would have the advantage of using the same architecture for both types of cognitive processes.[15]

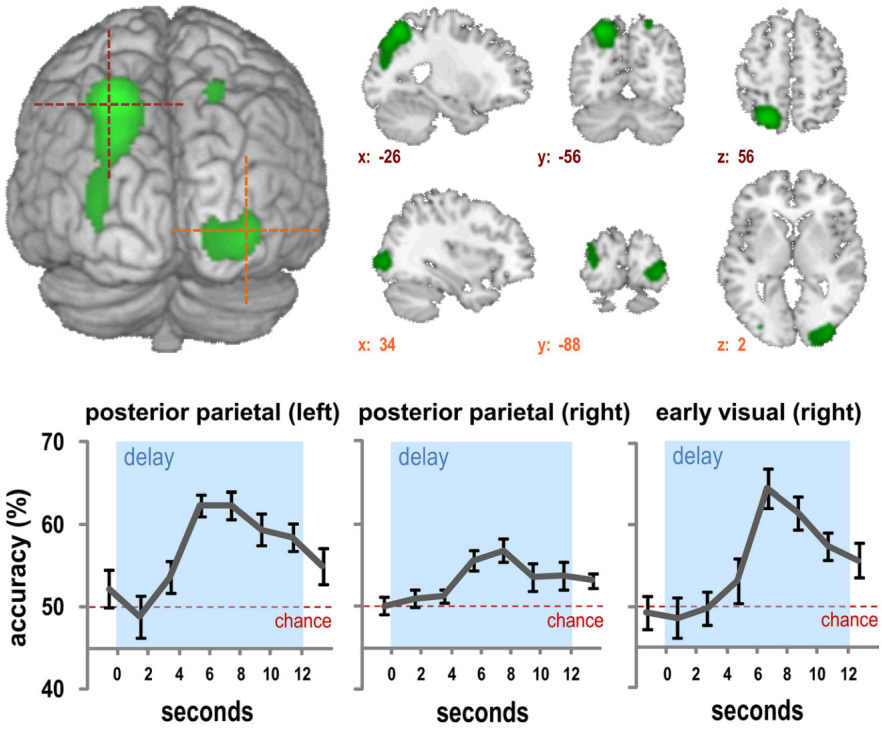

Figure 10 Results of Study 3, demonstrating a representation of the memorized visual short-term memory content in early visual, but also posterior parietal cortex (top panel). The prediction accuracy of the items held in memory varied across time, but was robust throughout the delay period (bottom panel).

[15] In fact, it could also be that evidence is accumulated in primary sensory brain regions which would also confirm the "same architecture" view. On the other hand, current evidence from monkey electrophysiology speaks against this interpretation (Britten et al., 1996; Salinas et al., 2000). In addition, a representation of DVs in a non-sensory format would be less susceptible to disturbance through other incoming stimuli.

In our third study (Christophel et al., 2012) we investigated which brain regions carry information about the remembered stimulus. A representation of this content in PPC would speak in favor of a shared representation of memory and perceptual decisions. We used a delayed match-to-sample task in which subjects had to remember one of four complex artificial color patterns. Complex color patterns were used to prevent storage in a non-visual format. Two of these stimuli were shown successively at the beginning of each trial, and a retro-cue indicated which of them had to be maintained in short-term memory. After a delay, two new stimuli were shown which were more or less similar to the remembered stimulus, and subjects had to indicate which one they thought to be more similar. Information about the representation of the stimuli was investigated using a searchlight analysis, time-resolved across the entire delay period.

We found information about the remembered content in early visual cortex and posterior parietal cortex (Figure 10). The representation of the content of VSTM in early visual cortex is consistent with previous findings (Harrison and Tong, 2009; Serences et al., 2009). We extend these results by showing a representation of memorized stimuli in brain regions that are not predominantly sensory. At the same time, the absence of a signal indicating storage in prefrontal cortex suggest that this brain region is predominantly involved in the access to VSTM (McNab and Klingberg, 2007; Edin et al., 2009).

Taken together, these results suggest that in addition to early visual cortex, PPC carries a representation of visual information stored in short-term memory. This representation could possibly take the form of a visual salience map (Koch and Ullman, 1985; Nothdurft, 2000) which indicates the importance of attending to each spatial location of the stimulus (Itti and Koch, 2000). This attentional importance is closely related to eye-movements (Itti, 2005) and thus provides a subtle link to the intentional framework of perceptual decision-making (Shadlen et al., 2008). In this framework, perceptual decisions reflect the intention of the agent, for example to perform an eye-movement. If this saliency representation is maintained, the subject could in fact store the picture in form of a sequence of eye movements that indicate visual search along the stimulus of interest.

Future studies should pinpoint whether the representational format in VSTM tasks in PPC reflects a representation of the stimulus itself, the salience of the stimulus, or a different variable. Additional research is also needed to elucidate the connection between storage of VSTM and perceptual DVs within the same experiment. This would greatly aid our understanding of the neuronal mechanisms subserving perceptual decision-making.

4. General discussion

In this dissertation, we investigated the neuronal mechanisms underlying perceptual decision-making and confidence in humans. In Chapter 1, we introduced the theoretical framework and important terminology and reviewed the existing literature on perceptual decision-making. In Chapter 2 we compared the specificity of monkey electrophysiology studies of perceptual decision-making to those employing functional imaging in humans and revealed a gap in the level of description of human fMRI studies, related to the low temporal and spatial resolution of this technique. We suggested that this gap could be bridged by increasing the functional specificity of the fMRI signal using MVPA. In Chapter 3, we report our own research carried out to investigate the neuronal structures involved in perceptual decision-making and confidence in humans. In particular, we focused on three aspects of perceptual decision-making. In the first study we showed which brain regions carry a representation of perceptual decisions in an abstract format and elucidated the differential involvement of early visual areas and posterior parietal cortex in demanding perceptual decisions. In the second study, we demonstrated a representation of the perceptual DV in various regions of the cerebral cortex and related this representation in the right vlPFC to a signal in the ventral striatum reflecting the confidence of the subject. In the third study, we demonstrated that posterior parietal cortex carried a representation of stimuli held in VSTM, in line with the idea that VSTM and perceptual decision making share neuronal resources.

4.1 Relationship between the first two studies of this thesis

Both in the first study ("abstract decisions") and in the second study ("decision variables and confidence") we investigated the neuronal representations of perceptual decisions. These studies share several key aspects: First, in both studies we employed a random dot motion discrimination task. Second, in both studies we decoded the perceptual choice from patterns of brain activity throughout the entire brain using a searchlight approach (Kriegeskorte et al., 2006; Haynes et al., 2007). Third, both studies used a response mapping screen to decorrelate perceptual choices from motor responses, revealing more abstract representations of perceptual decisions than those bound to motor responses. In both studies we could reveal patterns of brain activity reflecting the choice of the subject.

Although our studies shared these similarities, there were also differences in the design which might explain the slightly different patterns of results found in the two studies. Indeed, while in the first study choices were decoded only from early visual and left posterior parietal cortex only, large aspects of the cerebral cortex were shown to encode choices in the second study. Why did we find a representation of choices in early visual cortex in the first study, but not in the second? This seeming discrepancy might relate to the different stimulus characteristics of the random dot motion stimulus between the two studies. It has been shown previously that different stimulus characteristics of random dot motion stimuli can lead to largely varying behavioral responses (Pilly and Seitz, 2009). For that reason, it is no surprise that this difference can also lead the subjects to recruit different neuronal circuits depending on the task, for example when required to pool information from larger or smaller receptive fields. Another possibility is that the stimulus intensity used in Study 2 was not high enough to generate significant results at a whole-brain corrected level of statistical significance. While this readily explains the findings in early visual cortex, this does not explain why the left posterior parietal cortex showed decreasing responses in Study 1, which was not reported in Study 2. In fact, we could not investigate this relationship in Study 2, because we held the objective stimulus difficulty constant, while it was varied in Study 1. However, one might expect a similar relationship *within* a difficulty level for different levels of

confidence. To test for this relationship, we ran a post-hoc analysis on the data in Study 2, but found no region with a negative relationship between confidence and choice decoding accuracy. If it is true that the variation in confidence in Study 2 can be related to variations in performance across different levels of stimulus difficulty in Study 1, then this suggests that the variability in confidence in Study 2 is too small to mirror the much larger variation in stimulus difficulty in Study 1. Alternatively, as suggested in Chapter 3.1, the expectation of the subjects about the difficulty of the stimulus might lead them to recruit regions differently depending on the difficulty of the task. Since stimulus difficulty was always rather high in Study 2 and did not vary across trials, the strategy of adapting the accumulation mechanism to the task demands would not be helpful in this context. In contrast, the largely varying amounts of sensory evidence in Study 1 would encourage such adaptive strategies. The larger effects across the entire brain reflecting perceptual choices in Study 2 might relate (a) to the larger number of trials that entered decoding of choices than in Study 1 where each difficulty level was decoded separately, (b) the lower variability between trials related to the stimulation and (possibly) adaptive strategies, and (c) to the larger intertrial interval in the task that employed confidence ratings which could lead to better separation of the BOLD signal between trials.

In addition to the findings reported in the studies, this comparison of results indicates that abstract perceptual choices are encoded across multiple regions of the human brain and that the representation of perceptual choices depends not only on the difficulty of a given trial, but also on the expectation of the difficulty across trials.

4.2 Broader implications of the studies of this thesis

Previous studies investigating perceptual decision-making in humans have often relied on mean changes in the BOLD signal amplitude to infer the representation of perceptual decisions. We showed in Chapter 2 that this approach does not necessarily lead to findings that are specific to perceptual decisions, but could also reflect other, more general cognitive

functions such as performance monitoring, selective attention, or processes related to self-referential thought (Fox et al., 2005; Buckner et al., 2008). In the studies reported in Chapter 3, we used MVPA in a searchlight framework to decode patterns of brain activity related to behavioral choices and memorized stimuli. With that approach we showed in Study 1 for the first time how abstract perceptual choices are represented in the human brain. Our findings can help distinguishing between two alternative conceptions of perceptual decisions, one assuming that perceptual decisions are encoded in a motor-related code (Shadlen et al., 2008), and the other that perceptual decisions are calculated elsewhere in a more abstract format and are only relayed to motor structures. Current monkey electrophysiology studies cannot make this distinction (see Chapter 1.7). The brain regions found in our study, in particular the left PPC, can serve as a basis for future studies investigating the representational format of abstract perceptual choice. These studies should use MVPA to compare the representation of perceptual decisions that can be immediately translated into a motor plan to those where concurrent motor planning is not possible. If the same brain region is present in both tasks and shows a specific connection to a DV in a motor-related brain region *only* when the motor response is known in advance, this would demonstrate that brain regions allegedly carrying a representation of the DV might in fact only reflect a response that was computed in a more abstract fashion elsewhere in the brain. In addition, the finding that a brain region can show decreasing choice-specific responses is surprising and deserves further investigation. Possibly – supported by the results from Study 2 – this points towards more adaptive accumulation mechanisms which depend on the difficulty of the task (Philiastides et al., 2006; Philiastides and Sajda, 2007).

In the second study, by using signal detection theory (SDT) we demonstrated the representation of the DV and confidence in the human brain. These results support SDT as a model that bridges the gap between perceptual decision-making and confidence, by assuming a simple transformation between a DV in left vlPFC and confidence in the ventral striatum. The approach developed in our study sets the stage for the investigation of numerous other forms of decision confidence in future neuroimaging studies – for example

memory confidence or confidence about value-based choices – which may reveal important differences in the underlying transformation. Finally, by mapping out the neuronal structures involved in the computation of DVs and perceptual confidence throughout the whole human brain, our results can guide future neurophysiological studies aimed at characterizing the dynamics of DVs and of choice-independent confidence signals, and their transformation, in greater detail, to shed more light on the underlying mechanism.

In the third study, we showed that early visual cortex and PPC carry a representation of the content of VSTM. This result significantly helped to distinguish between different theories of VSTM storage and showed evidence for storage in brain regions also involved in processing stimuli (early visual cortex) and their spatial relationship (PPC). From the perspective of perceptual decision-making, this result can be seen as a first step towards answering questions of how the storage of memorized items in PPC can be related to the representation of a DV in the same region.

4.3 Closing comments and outlook

In the history of science great advances have often followed the introduction of new research methodology. This methodology allowed addressing questions that previously could not be answered, and possibly also questions that had not been asked previously. One such great advance was the introduction of MVPA in the searchlight framework to the analysis of BOLD fMRI signals (Haxby et al., 2001; Kriegeskorte et al., 2006; Haynes et al., 2007). The results presented in this thesis all rely on the increased sensitivity and specificity brought about by this technique. The questions raised in this thesis would have been much more difficult – if not impossible – to address with different currently available methodology of brain imaging data analysis.

Still, there is a long way to go. Even with MVPA, fMRI suffers from low temporal resolution. It remains open how information from EEG or MEG can possibly be integrated with fMRI without losing the high specificity gained through the use of MVPA. In addition,

MVPA can only investigate the amount of information buried in a particular brain region, but is non-directional (Jimura and Poldrack, 2012) and most often does not allow answering questions about the exact representational format in a particular brain region (Kay et al., 2008; Mitchell et al., 2008; Kriegeskorte et al., 2008; Diedrichsen et al., 2013). These challenges naturally put a damper on the development of the understanding of the brain mechanisms underlying perceptual decision-making in humans.

On the other hand, we hope to have shown that it is possible with the currently available methodology to significantly increase our knowledge about how humans carry out perceptual decisions, compute confidence, and represent items in VSTM, if only the right questions are asked. These methods – combined with clever research paradigms – will in the future guide our understanding of the brain mechanisms underlying cognitive processes and will hopefully refine our understanding of these processes under investigation.

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6. Research articles

Study 1:

Hebart MN, Donner TH, Haynes J-D (2012) Human visual and parietal cortex encode visual choices independent of motor plans. Neuroimage 63:1393–1403.

Study 2:

Hebart, MN, Schriever Y, Donner TH, Haynes J-D (submitted) The relationship between perceptual decision variables and confidence in the human brain.

Study 3:

Christophel TB, Hebart MN, Haynes J-D (2012) Decoding the contents of visual short-term memory from human visual and parietal cortex. J Neurosci 32:12983–12989.

Statement of Authorship

I hereby certify that this dissertation has been composed by me and is based on my own work, unless stated otherwise. Ideas and thoughts cited directly or indirectly from other work have been cited accordingly.

23.07.2013 _____

Date signed Signature